Speech: Current Features & Extraction Methods

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Editor

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UTM UNIVERSITI TEKNOLOGI MALAYSIA
Penerbit
UTM Press

www.penerbit.utm.my
2008

First Edition 2008

Perpustakaan Negara Malaysia Cataloguing-in-Publication Data

Speech : current features & extraction methods / editor Norlaili Mat Safri.
Includes index
ISBN 978-983-52-0650-4
1. Automatic speech recognition. 2. Signal processing. I. Norlaili Mat Safri.
621.384

Editor: **Norlaili Mat Safri**
Pereka Kulit: **Mohd Nazir Md. Basri & Mohd Asmawidin Bidin**

Diatur huruf oleh / *Typeset by*
Fakulti Kejuruteraan Elektrik

Diterbitkan di Malaysia oleh / *Published in Malaysia by*
PENERBIT
UNIVERSITI TEKNOLOGI MALAYSIA
34 – 38, Jln. Kebudayaan 1, Taman Universiti,
81300 Skudai,
Johor Darul Ta'zim, MALAYSIA.
(PENERBIT UTM anggota PERSATUAN PENERBIT BUKU MALAYSIA/
MALAYSIAN BOOK PUBLISHERS ASSOCIATION dengan no. keahlian 9101)

Dicetak di Malaysia oleh / *Printed in Malaysia by*
UNIVISION PRESS SDN. BHD.
Lot. 47 & 48, Jalan SR 1/9, Seksyen 9,
Jalan Serdang Raya, Taman Serdang Raya,
43300 Seri Kembangan,
Selangor Darul Ehsan, MALAYSIA.

CONTENTS

PREFACE

Praise to Allah the Almighty who gave us guidance, opportunity and strength to complete this book chapter.

This edition of *Speech: Features & Extraction Methods* contains 9 chapters where each chapter describes different methods in the extraction of speech features. The methods presented are a collection of speech extraction methods commonly used by researchers in the field and 2 newly introduced methods obtained from current research by the authors. This book is recommended for the usage in speech related research as well as other educational purposes. This compilation of research works is worth to look into and further develop for improvements based on the fundamental ideas illustrated throughout the chapters.

In the future we plan to compile our research works for speech recognition applications using these different extracted features.

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2008

1

LINEAR PREDICTIVE CODING

Rubita Sudirman
Ting Chee Ming

INTRODUCTION

Today, speech recognition can be considered as a mature technology, where current research and technologies have complex combinations of methods and techniques to work well with each other towards the refinement of the recognition. If for instance a neural network wanted to be used as the recognizer, one would intend to have a method that can reduce the network complexity with less storage requirement which in return it will give faster recognition.

LPC FEATURE EXTRACTION

The greatest importance of all recognition system is the signal processing which converts the speech waveform to some type of parametric representation (Rabiner and Shafer, 1978). This parametric representation is then used for further analysis and processing. In speech recognition, analysis can be done using MFCC, cepstrum or LPC (Rabiner and Schafer, 1978; Rabiner and Juang, 1993). However, in this research and chosen by many others (Sakoe *et al.*, 1989; Patil, 1998; Zbancioc and Costin, 2003), LPC is used due to its ability to encode speech at low bit rate and can provide the most accurate speech parameters, so that least information is lost during the procedure. LPC also showed good performances in speech recognition applications. Linear predictive analysis of speech has become the predominant technique for estimating the basic parameter of speech. It provides both an accurate estimate of the speech parameters and also an efficient computational model of speech.

The modern day LP extractor consists of five major blocks: pre-emphasis, frame blocking, windowing, autocorrelation analysis and LPC computation. These are the procedures to calculate the LPC coefficients and they are shown in Fig. 1.1. Each block in the figure is described in the following sections.

PRE-EMPHASIS

Pre-emphasis is done to improve the signal-to-noise ratio (SNR), it also increases the magnitude of the higher signal frequencies. The front end process the speech signal using Linear Predictive Coding (LPC) to obtain the coefficients, which represent its feature. The first step to the process is to pre-emphasize the signal so that the signal is spectrally flatten and make it less susceptible to finite precision effects later in the signal processing. The pre-emphasis is using the widely used first-order system as follows:

$$x(n) = x(n) - 0.95x(n-1) \tag{1.1}$$

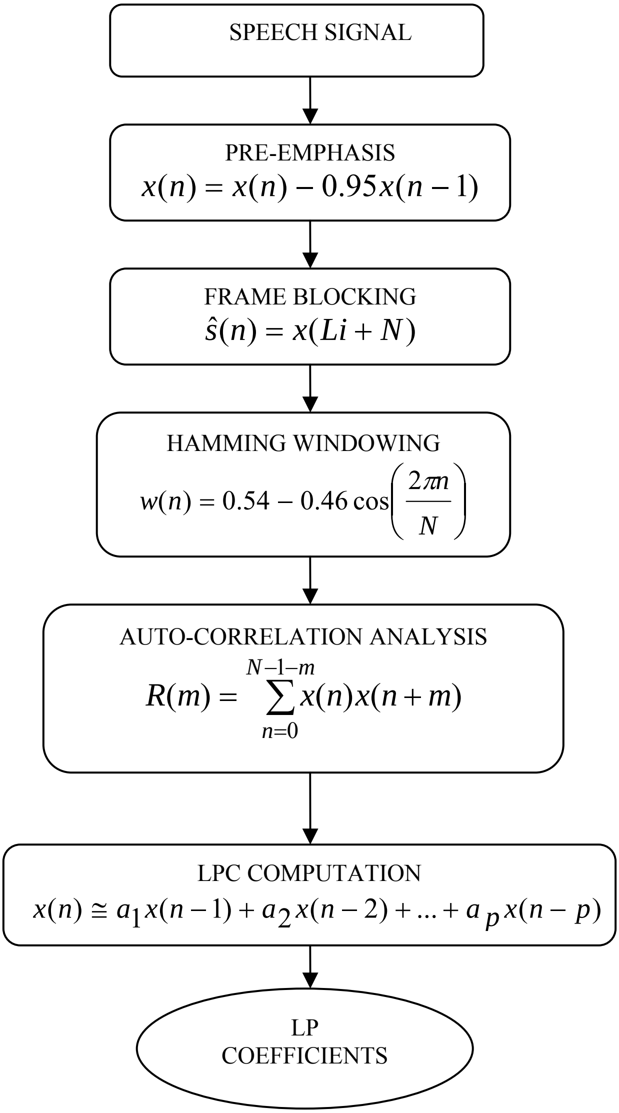
SPEECH SIGNAL
PRE-EMPHASIS
$x(n) = x(n) - 0.95x(n-1)$
FRAME BLOCKING
$\hat{s}(n) = x(Li + N)$
HAMMING WINDOWING
$w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N}\right)$
AUTO-CORRELATION ANALYSIS
$R(m) = \sum_{n=0}^{N-1-m} x(n)x(n+m)$
LPC COMPUTATION
$x(n) \cong a_1 x(n-1) + a_2 x(n-2) + ... + a_p x(n-p)$
LP
COEFFICIENTS

Fig. 1.1 Flow diagram of LPC process

FRAME BLOCKING

The result from the pre-emphasized signal is divided to equal length frames of length N. The start of each frame is offset from the start of the previous frame by L samples. The start of the second frame begins at L and the third would begin at 2L and so on. But, if L≤N, then adjoining frames will overlap and the LP spectral estimates will show a high correlation. In this research, the sampling frequency is 16 kHz, with average frame of 40 and overlap of 10 ms. If we define x_i as the ith segment of the sampled speech s and I frames are required then the frame blocking process can be described as

$$\hat{s}(n) = x_i(Li + N), \quad n = 0,1,2,\ldots,\mathrm{N} - 1, \;\; i = 0,1,2,\ldots,\mathrm{I} - 1 \tag{1.2}$$

WINDOWING

The purpose of windowing generally is to enhance the quality of the spectral estimate of a signal and to divide the signal into frames in time domain. Thus, after pre-emphasis, the signal is windowed using the commonly used Hamming window function to fit the purpose mentioned, where *N* is the length of the window. The Hamming window used is written as

$$w(n) = 0.54 - 0.46\ \cos\left(\frac{2\pi n}{N-1}\right), \qquad \text{for } 0 \le n \le N\text{-}1 \tag{1.3}$$

LPC COEFFICIENTS COMPUTATION

Fundamental criteria of an LPC model for a sample speech at time n, denoted as x(n) is an approximation of a linear combination of previous samples, which is represented as

$$x(n) \cong a_1 x(n-1) + a_2 x(n-2) + \ldots + a_p x(n-p) \tag{1.4}$$

where $a_1, a_2, \ldots, a_p$ are coefficients which was assumed to be constant for each speech frame.

To make an exact approximation to the speech signal *x(n)*, an error term which is the excitation of the signal is included as a filtering term to Equation (1.4). *G* is the excitation gain and *u(n)* is the normalized excitation.

$$x(n) = \sum_{k=1}^{p} a_k x(n-k) + Gu(n) \tag{1.5}$$

Using z-transform, Equation (1.5) becomes

$$X(z) = \sum_{k=1}^{p} a_k z^{-i} X(z) + GU(z) \tag{1.6}$$

So the transfer function, H(z) is

$$H(z) = \frac{X(z)}{GU(z)} = \frac{1}{1 - \sum_{k=1}^{p} a_i z^{-i}} = \frac{1}{A(z)} \tag{1.7}$$

Then, the estimated *x(n)* which is also the linear combination of previous samples, is define as

$$\hat{x}(n) = \sum_{k=1}^{p} a_k x(n-k) \tag{1.8}$$

The prediction error is the difference between the real signal and the estimated signal:

$$e = x(n) - \hat{x}(n) = x(n) - \sum_{k=1}^{p} a_k x(n-k) \tag{1.9}$$

The error over a speech segment is defined as

$$E_n = \sum_m e_n^2(m) = \left[\sum_m x_n(m) - \sum_{k=1}^{p} a_k x_n(m-k) \right]^2 \tag{1.10}$$

The next step is to find a_k by taking the derivative of E_n with respect to a_k and set them to zero.

$$\frac{\partial E_n}{\partial a_k} = 0 \quad \text{for } k=1, 2, \ldots, p. \tag{1.11}$$

This brings Equation (1.10) to

$$\sum_{k=1}^{p} a_k \sum_m s_n(m-i) s_n(m-k) = \sum_m s_n(m) s_n(m-i) \tag{1.12}$$

The calculation for a_k which is $a_1, a_2, .., a_p$ will utilize autocorrelation through Durbin's algorithm described next.

AUTOCORRELATION

The windowed signal then go through the autocorrelation process, which is represented in Equation (1.13), *p* is the order of LPC analysis. This is based on the estimated time average autocorrelation.

$$\hat{R}(m) = \sum_{n=0}^{N-1-m} x(n)x(n+m), \qquad \text{for } m = 0,1,2,.., p \qquad (1.13)$$

$x_n(n)$ is the windowed signal, where $x_n(n)=x(n)w(n)$.

In matrix form, the set of linear equations can be expressed as:

$$\begin{bmatrix} R_m(0) & R_m(1) & R_m(2) & \cdots & R_m(p-1) \\ R_m(1) & R_m(0) & R_m(1) & \cdots & R_m(p-2) \\ R_m(2) & R_m(1) & R_m(0) & \cdots & R_m(p-3) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ R_m(p-1) & R_m(p-2) & R_m(p-3) & \cdots & R_m(0) \end{bmatrix} \begin{bmatrix} \hat{a}_1 \\ \hat{a}_2 \\ \hat{a}_3 \\ \cdots \\ \cdots \\ \hat{a}_p \end{bmatrix} = \begin{bmatrix} R_m(1) \\ R_m(2) \\ R_m(3) \\ \cdots \\ \cdots \\ R_m(p) \end{bmatrix} \qquad (1.14)$$

The common LPC analysis is using Durbin's recursive algorithm, which is based on Equations (1.15)-(1.20) and result of matrix equation in (1.14):

$$E^{(0)} = R(0) \tag{1.15}$$

$$k_i = \frac{R(i) - \sum_{j=1}^{i-1} a_j^{(i-1)} R(i-j)}{E^{(i-1)}}, \quad for \quad 1 \le i \le p \tag{1.16}$$

$$a_i^{(i)} = k_i \tag{1.17}$$

$$a_j^{(i)} = a_j^{i-1} + k_i a_{i-j}^{i-1}, \qquad \text{for} \quad 1 \le j \le i-1 \tag{1.18}$$

$$E_i = (1 - k_i^2) E_{i-1} \tag{1.19}$$

These equations are solved recursively for $i = 0, 1, \ldots, p$, where p is the order of the LPC analysis. Then, the final solution is when $i = p$, which is

$$a_j = a_j^p, \quad \text{for } 1 \le j \le p \tag{1.20}$$

BURG'S METHOD

The Burg's method for auto-regression spectral estimation is based on minimizing the forward and backward prediction errors while satisfying the Levinson-Durbin recursion. In contrast to other auto-regression estimation methods like the Yule-Walker, the Burg's method avoids calculating the autocorrelation function, and instead estimates the reflection coefficients directly.

Let assume $f_p(n) = e_p^+(n)$ (forward prediction) and let $r_p(n) = e_p^-(n)$ (backward prediction). k_p is calculated by minimizing the sum of the squares of the forward and backward prediction errors over the window, which is

$$E = \frac{1}{2(N-P)} \sum_{j=p}^{N-1} f_p^2(j) + r_p^2(j+1) \tag{1.21}$$

and

$$E = \frac{1}{2(N+P)} \sum_{j=p}^{N-1} \left[f_{p-1}(j) + k_p r_{p-1}(j) \right]^2 + \left[r_{p-1}(j) + k_p f_{p-1}(j) \right]^2 \tag{1.22}$$

where k_p is the desired partial correlation coefficient and $f_{p\ 1}$ and r_{p-1} are known from the previous pass. Error minimization can be done by differentiating the error in Equation 1.22.

After simplification, the differentiation is:

$$\frac{\partial E}{\partial k_p} = \frac{1}{N-P} \sum_{j=p}^{N-1} k_p \left[f_{p-1}^2(j) + r_{p-1}^2(j) \right] + 2 f_{p-1}(j) r_{p-1}(j) \tag{1.23}$$

Setting the derivative to zero gives the following recursive formula for k_p:

$$k_p = -\frac{2P}{Q} \tag{1.24}$$

where $$P = \sum_{j=p}^{N-1} f_{p-1}(j) r_{p-1}(j) \tag{1.25}$$

and $$Q = \sum_{j=p}^{N-1} f_{p-1}^{2}(j) r_{p-1}^{2}(j) \tag{1.26}$$

Once the reflection coefficient is determined, the predictor coefficients can be calculated. If the autocorrelations are required, Burg's shows that R_p can be estimated by applying the new order-*p* predictor to the previous estimates $R_0, R_1, \ldots, R_{p-1}$ which is:

$$R_p = -\sum_{i=1}^{p} a_p(i) R_{p-1} \tag{1.27}$$

The primary advantages of the Burg method are resolving closely spaced sinusoids in signals with low noise levels, and estimating short data records, in which case the AR power spectral density estimates are very close to the true values (Parsons, 1986). However, the accuracy of the Burg method is lower for high-order models, long data records, and high signal-to-noise ratios. The spectral density estimate computed by the Burg method is also susceptible to frequency shifts (relative to the true frequency) resulting from the initial phase of noisy sinusoidal.

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2

HIDDEN MARKOV MODEL

Rubita Sudirman
Ting Chee Ming
Hong Kai Sze

INTRODUCTION

In this chapter, the Hidden Markov Model which is a well-known and widely used statistical method for characterizing the spectral properties of the frames of a pattern is presented. The basic theory of Markov chain have been known to mathematicians and engineers for more than 80 years ago, but it is only in the past few decades that it has been applied to speech processing [Rabiner, 1989]. The basic theory of Hidden Markov Models was published in a series of classic papers by Baum and his colleagues in the late sixties and early seventies and was implemented for speech processing applications by Baker at CMU and by Jelinek and his colleagues at IBM in the 1970s (Rabiner and Juang, 1993).

Processes from the real world usually produce outputs that can be observed and these outputs are characterized as signals. The signal can be discrete, such as characters from an alphabet and quantized vectors from a codebook. Alternatively, the signal can be continuous, for example speech samples, temperature measurements, music etc. Signal can be either stationary or non-stationary. It can be pure or contains noise or corrupted by transmission of distortions and reverberation (Rabiner, 1989).

Chapter 1 has described that speech is a time-varying process that has been modelled with linear systems, such as LPC analysis.

This is done by assuming that every short-time segment of observation is a unit with a pre-chosen duration (Rabiner and Juang, 1993). On most physical systems, the duration of short time segment is determined empirically. The concatenation of these short units of time makes no assumptions about the relationship between adjacent units. Temporal variation can either be big or small. The template approach is proven to be useful and becomes the fundamental of many speech recognition systems.

The template method, albeit its usefulness, may not be the most efficient technique. Many real world processes are observed to have a sequential changing behaviour. The properties of the process are commonly held steadily with minor fluctuations, for a certain period, then at certain instances, change to another set of properties. The opportunity for more efficient modelling can be exploited if these periods of quasi steady behaviour are first identified. Secondly, assumption has to be made that temporal variations within each of these steady periods can be represented statistically [Rabiner, 1989]. Hidden Markov model is a more efficient representation that can be obtained using a common short-time model for each of the steady part of the signal, along with some characterizing of how one such period evolves to the next.

DEFINITION OF HMM

According to Rabiner and Juang (1993), hidden Markov model is a doubly embedded stochastic process with an underlying stochastic process that is not directly observable (it is hidden) but can be observed only through another set of stochastic processes that produce the sequence of observations.

An example from Rabiner (1989) is adapted and presented here to illustrate the idea of HMM. Try to imagine the following scenario. Let’s say you are in one room with a curtain that you cannot see what is happening through the curtain.

On the other side is a person who is doing a coin-tossing experiment with a few coins. The person does not let you know which coin he selects at any time. Instead he tells you the result of each coin flip. Thus a sequence of hidden coin-tossing experiments is performed, with the observation sequence consists a series of heads and tails. Here you observe the coin tossing result as follow:

O = (HTTHTHHHTTT…T), where H stands for heads and T stands for tails.

From the experiment above, the problem is how we want to build an HMM to explain the observed sequence of results. One possibility is by considering the experiment is performed using a '2 biased coins', the possibilities are shown in Fig. 2.1.

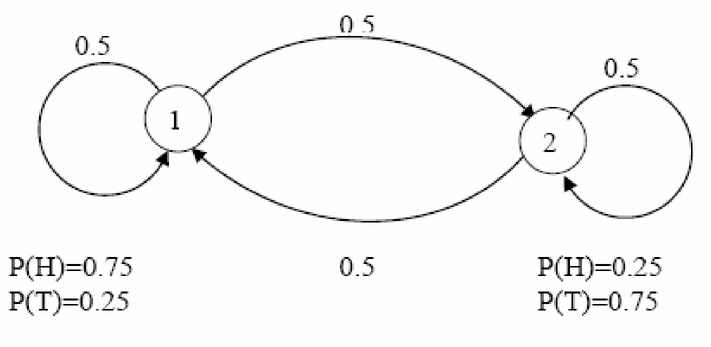

Fig. 2.1 Two Biased Coin Model

In Fig. 2.1, there are 2 states, and each state represents a coin. In state 1, the probability for the coin to produce a head is 0.75 while the probability for it to produce a tail is 0.25. In state 2, the probability to produce head is 0.25 while the probability to produce tail is 0.75. The probability of leaving and re-entering both states is 0.5. Here we associate every state with a biased coin. Now we consider the HHT tossing experiment. We assume that the 1st H is thrown using the 1st coin, the 2nd H with the 2nd coin and the T is thrown using the 2nd coin. Now we calculate the probability for it to happen with the assumption that this person starts with the 1st coin. The answer is (1 × 0.75) × (0.5 × 0.25) × (0.5 × 0.75) = 0.03516. For the second case, if the first 2 H are thrown using the 1st coin while T is thrown with the 2nd coin, the probability for it to happen is (1 × 0.75) × (0.5 × 0.75) × (0.5 × 0.75) = 0.1055. Here we notice that using a different model, the probability of getting the same observations becomes different.

There are a few important points about the HMM. First, the number of states of the model needs to be decided. However, the decision is difficult to make without a priori information about the system, thus sometimes trial and error is needed before the most appropriate model size is known. Second, the model parameters such as state transition probabilities and the probabilities of heads and tails in each state) need to be optimized to best represent the real situation. Finally, the size of sequence cannot be too small, if this happens, the optimal model parameters cannot be estimated [Rabiner and Juang, 1993].

ELEMENT OF AN HMM

The example from the previous section gives the idea of what HMM is and how it can be applied in that simple scenario. The elements of a HMM need to be defined as explained in Rabiner and Juang (1993).

The discrete density HMM is characterized as follow:

(i) The number of states in the model, N. In the coin-tossing experiments, each distinct biased coin represents one state. Usually the states are interconnected in such a way that every state can be reached by the others. This is called an ergodic model. The individual states are labelled as {1, 2, …., N} and the state at time t is denoted as q_t.

(ii) The number of distinct observation symbols per state, M. The observation symbols represent the physical output of the modelled system. In the coin-tossing experiment, the observation symbols are heads and tails. The individual symbols are denoted as V = {v_1, v_2, …, v_M}

(iii) The state transition probability distribution, A = {a_{ij}} which can be expressed in the following form:

$$a_{ij} = P\left[q_{t+1} = j \middle| q_t = i\right] 1 \leq i, j \leq N \tag{2.1}$$

(iv) The observation symbol probability distribution, B={$b_j(k)$} which can be expressed in the form below:

$$b_j(k) = P\left[o_t = v_k \middle| q_t = j\right], 1 \leq k \leq M \tag{2.2}$$

(v) The initial state distribution π = {π_i} in which

$$\Pi_i = P\left[q_1 = i\right] 1 \leq i \leq N \tag{2.3}$$

THREE PROBLEM OF HMM

There are three key problems of interest that must be solved in order to apply HMM into the real applications. These problems are described in [Rabiner and Juang, 1993], [Rabiner, 1989] and [3].

Problem 1: Given the observation sequence O=$O_1O_2…O_t$ and a model λ=(A,B,Π), how do we efficiently compute P(O, λ), the probability of the observation sequence, given the model?

This is an evaluation problem. This can be viewed as getting a score on how well a given model matches a given observation sequence. This is useful but we need to choose among several competing models.

Problem 2: Given the observation sequence $O=O_1O_2\ldots O_t$ and a model λ, how do we choose a corresponding state sequence $Q=q_1q_2\ldots q_t$ which is optimal in some meaningful sense, for example, it is most suitable to explain the observations?

The second problem is the one in which we attempt to uncover the hidden part of the model to find the correct state sequence. However there is usually none to be found. In practical situations, the optimality criterion is usually used to best solve the problem as good as possible. For continuous speech recognition, the learning model structure is used to determine the optimal state sequences and compute the average statistics of the individual states.

Problem 3: How to adjust the model parameters $\lambda=(A,B,\Pi)$ such that $P(O, \lambda)$ is maximized?

The third problem is the problem of optimizing the model parameters to best describe the given observation sequences and this is known as the training problem.

SOLUTION TO THE PROBLEM

The solutions to the aforementioned three problems are the key steps in applying HMM in speech recognition systems. Here the formal mathematical solutions for each problem for HMM are adapted from Rabiner (1989).

Problem 1

The probability of the observation sequence needs to be calculated, given the model parameters. Thus the simplest solution is to enumerating every possible state sequence of length T (the number of observations). A fixed state sequence Q ($Q=q_1q_2\ldots q_T$) is selected and the probability of the observation sequence O is given by the following equation:

$$P(O|Q,\lambda) = b_{q_2}(O_1) \bullet b_{q_2}(O_2) \ldots b_{q_T}(O_t) \tag{2.4}$$

while the probability of such a state sequence Q happens is given by the following:

$$P(Q,\lambda) = \Pi_{q_1} a_{q_1q_2} a_{q_2q_3} \ldots\ a_{q_{T-1}q_T} \tag{2.5}$$

Then the product of both probabilities represented by that is P(O,Q|λ), the probability of the observation sequence happening with the state sequence Q. To calculate P(O|λ), calculations have to be made for every possible state sequence Q, then summing up all possibilities together. This calculation is computationally unfeasible, even for small value of N and T. Thus a more efficient procedure is required to solve Problem 1.

The method is called forward-backward procedure. Here the forward variable $\alpha_t(i)$ is defined as the probability of the partial observation sequence $O_1, O_2, \ldots O_t$ (until time t) and state i, at time t, given the model λ and can be calculated using the Forward Procedure:

Initialization:

$$\alpha_1(i) = \Pi_i b_i(O_i), 1 \le i \le N \tag{2.6a}$$

Induction:

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(O_{t+1}), 1 \le t \le T-1, 1 \le j \le N \tag{2.6b}$$

Termination:

$$P(O|\lambda) = \sum_{i=1}^{N} \alpha_T(i) \tag{2.6c}$$

Step 1 actually initializes the forward probability of the initial observation O_1. The induction step is illustrated below, which shows how the state s_j is reached at time t+1 from the N possible state q_i, i=1,2,…,N at time t.

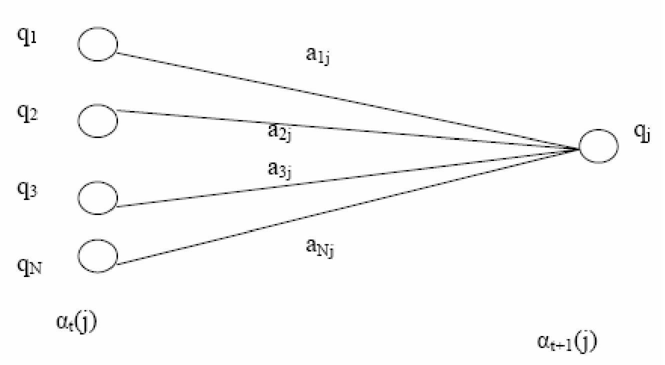

Fig. 2.2 Forward procedure

$\alpha_t(i)$, the probability of $O_1,O_2,...O_t$, are observed and the state stops at q_i at time t, and the product $\alpha_t(i)a_{ij}$ is the probability of the event that $O_1,O_2,...O_t$, are observed and the state stops at q_j at time t+1 via state q_i at time t. Adding up these products over all N possible states, at time t result in the probability of q_j at time t+1 with all the accompanying previous partial observations. After this is done, the summation is multiplied with $b_j(O_{t+1})$, which means the probability of O_{t+1} happening at state q_j at time t+1 with all accompanying previous partial observations. The last termination step gives the desired final result $P(O|\lambda)$ as the sum of all terminal forward variables.

The forward procedure needs fewer computations. It involves only N(N+1)(T+1)+N multiplications and N(N-1)(T-1) additions calculations.

Similarly, the backward variable β, which represents the probability of the partial observation sequence from t+1 to the end, given state i at time t and model λ, can be calculated as follows:
Initialization:

$$\beta_T(i) = 1 \qquad 1 \le i \le N \tag{2.7a}$$

Induction:

$$\begin{aligned}&\beta_T(i) = \sum a_{ij} b_j(O_{t+1})\beta_{t+1}(j),\\ &t = T-1, T-2, \ldots\ldots, 1\\ &1 \le i \le N\end{aligned} \tag{2.7b}$$

The first step defines all $\beta_T(i)$ to be 1. The induction step can be illustrated as shown in Fig. 2.3. It shows that in order to have been in state q_i at time t, and to account for the rest of the observation sequence, transition has to be made for every N possible states at time t+1, accounted for the observation symbol O_{t+1} in that state, and this account for the rest of the observation sequence.

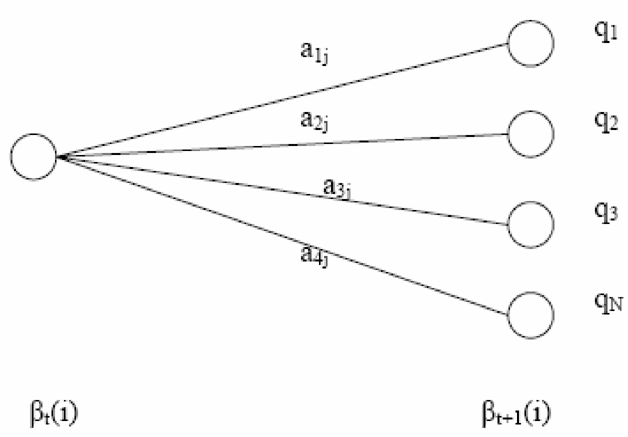

Fig. 2.3 Backward Procedure

Problem 2

There are several possible ways to solve this problem, since there are a few possible optimally criteria. One possible optimality criterion is by choosing the states, it, that are individually most likely. By doing this the expected number of correct individual states is maximized.

A new variable γ can be defined such that:

$$\gamma_t(i) = p(i_t = q_i | O, \gamma) \tag{2.8}$$

which represents the probability of being in state i at time t, given the observation sequence O, and the model λ. In term of the forward and backward variable, it can be expressed as:

$$\lambda_i(t) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i)\beta_t(i)} \tag{2.9}$$

Because the α accounts for $O_1O_2...O_t$, and state q_i at time t, while β accounts for $O_{t+1}O_{t+2}...O_T$ given the state q_i at time t. The normalization factor P(O|λ) makes $\gamma_i(t)$ a conditional probability. Using $\gamma_i(t)$, the individual most likely, it, at time t is:

$$q_t = \arg\min_{1<i<N} [\gamma_t(i)], 1 \le t \le T \tag{2.10}$$

However, finding the optimal states might be a problem, especially when there are disallowed transitions. The optimal state obtained from this way may be an impossible state sequence since it simply looks for the most likely state at every instance without regarding to the global structure, neighbouring state and the length of the observation sequence.

The disadvantage of the above methods is the need of global constraint on the derived optimal state sequence. Another optimality criteria may be used to determine the single best path with the highest probability, by maximizing P(O,I|λ). A formal method to find this single best state sequence is by using the Viterbi Algorithm.

Initialization:

$$\delta_t(i) = \Pi_i b_i(O_1) \qquad 1 \le i \le N \qquad (2.11a)$$

$$\varphi_1(i) = 0$$

Recursion:

$$\delta_t(j) = \max_{1<i<N}\left[\delta_{t-1}(i)a_{ij}\right]b_j(O_t) \qquad \begin{matrix} 2 \le t \le T \\ 1 \le j \le N \end{matrix} \qquad (2.11b)$$

$$\varphi_t(j) = \arg\max_{1<j<N}\left[\delta_{t-1}(i)a_{ij}\right] \qquad \begin{matrix} 2 \le t \le T \\ 1 \le j \le N \end{matrix}$$

Termination:

$$P = \max_{1<j<N}\left[\delta_T(i)\right] \qquad (2.11c)$$

Alternatively, the logarithms version can be used:

Initialization:

$$\begin{matrix} \delta_t(i) = \log(\Pi_i) + \log(b_i(O_i)) \\ \varphi_1(i) = 0 \end{matrix} \qquad 1 \le i \le N \qquad (2.12a)$$

Recursion:

$$\delta_t(j) = \max_{1<j<N}\left[\delta_{t-1}(i) + \log(a_{ij})\right] + \log(b_j(O_t)) \tag{2.12b}$$

$$2 \le t \le T, 1 \le j \le N$$

$$\varphi_t(j) = \arg\max_{1<j<N}\left[\delta_{t-1}(i) + \log(a_{ij})\right]$$

$$2 \le t \le T, 1 \le j \le N$$

Termination:

$$P = \max_{1<j<N}\left[\delta_T(i)\right] \tag{2.12c}$$

The calculation required for this alternative implementation is N2T additions. It does not need multiplications, thus making it more computationally efficient. The logarithmic model parameters can be calculated once and saved, thus the cost of finding the logarithms is negligible.

Problem 3

The third problem is to readjust the model parameters {A,B,π} to maximize the probability of the observation, when the model is given. This is the most difficult problem and there is no known way of solving the maximum likelihood model analytically. Hence, an iterative procedure, such as the Baum-Welch method, or gradient techniques must be used for optimization. Iterative Baum-Welch method is discussed here.

First, a new variable $\xi_t(i,j)$ is defined which represents the probability of being in state i at time t and state j at time t+1, given the observation sequence O. The illustration of this process is in Fig. 2.4.

$$\xi_t(i,j) = P(q_t = i, q_{t+1} = j | O, \lambda) \tag{2.13}$$

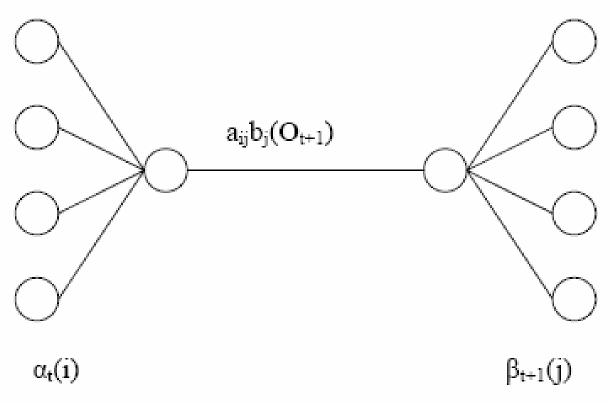

Fig. 2.4 Illustration of probability state

Thus we can write ζ_t(i,j) as:

$$\xi_t(i,j) = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)}{P(O|\lambda)} = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)} \tag{2.14}$$

and γ, is the probability of being in state i at time t:

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j) \tag{2.15}$$

Thus the re-estimation formulas of probability parameters are as follow:

$$\overline{\pi_j} = \gamma_1(i) \tag{2.16a}$$

$$\overline{a_{ij}} = \frac{\sum_{t=1}^{T-1} \xi_t(i, j)}{\sum_{t=1}^{T-1} \gamma_t(i)} = \frac{\sum_{t=1}^{T-1} \alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)}{\sum_{t=1}^{T-1} \sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)} \tag{2.16b}$$

$$\overline{b_j}(k) = \frac{\sum_{\substack{t= \\ s,t,o_t=v_k}}^{T} \sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)}{\sum_{t=1}^{T} \sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)} \tag{2.16c}$$

The re-estimation of π simply means the number of times in state i at time t=1. The re-estimation of a_{ij} is the expected number of transitions from state i to state j divide by expected number of transitions from state i. The $b_j(k)$ is re-estimated using the expected number of time in state j and observation symbol v_k divided by the expected number of times in state j.

If initial model is defined as λ and the re-estimation model as λ’, then λ’ is the more likely model in the sense that P(O| λ’)>P(O| λ). This means another model that the observation sequence is more likely to be produced have been found.

Iteratively using λ’ in place of λ and repeat the re-estimation calculation, the probability of O being observed is improved, until some limiting point is reached.

IMPLEMENTATION ISSUES WITH HMM

The discussion in the previous section has been around theory of HMM. In this section, several practical implementation issues are handled.

Scaling

For a sufficient long observation sequence, the dynamic range of $\alpha_t(i)$ computation can go beyond the precision range of any existing computer. There exists a scaling procedure that can be used to multiply the alpha values by a scaling coefficient which is independent of i. A similar scaling can also be done to the $\beta_t(i)$. Thus at the end the scaling coefficients are cancelled out.

Minimum Value for b_{jk}

A second issue is the use of finite set of training data for training the HMM model. If a symbol does not exist often in the observation sequence, the probability for that symbol in some states can become 0. This is not desirable because the probability score can become 0 because of that $b_j(k)$. One way to solve this is by setting a minimum value for $b_j(k)$.

Multiple Observation Sequence

The re-estimation formulas in the previous section consider only a single training observation sequence. However in the real applications, multiple observation sequences are usually available, then model parameters can be re-estimated by a little modifications.

$$\overline{a_{ij}} = \frac{\sum_{k=1}^{K} \frac{1}{P_k} \sum_{t=1}^{T-1} \alpha_t^k (I) a_{ij} b_j \left(o_{t+1}^k\right) \beta_{t+1}^k (j)}{\sum_{k=1}^{K} \frac{1}{P_k} \sum_{t=1}^{T-1} \sum_{j=1}^{N} \alpha_t (i) a_{ij} b_j \left(o_{t+1}\right) \beta_{t+1} (j)} \tag{2.17a}$$

$$\overline{b_j}(l) = \frac{\sum_{k=1}^{K} \frac{1}{P_k} \sum_{\substack{t=1 \\ s,t,o_t=v_t}}^{T-1} \alpha_t^k \sum_{j=1}^{N} \alpha_t (i) a_{ij} b_j \left(o_{t+1}\right) \beta_{t+1} (j)}{\sum_{k=1}^{K} \frac{1}{P_k} \sum_{t=1}^{T-1} \sum_{j=1}^{N} \alpha_t (i) a_{ij} b_j \left(o_{t+1}\right) \beta_{t+1} (j)} \tag{2.17b}$$

From the above equations, observe that the modified re-estimation formulas are actually a summation of the individual re-estimation for each training observation sequence divided by the individual probability for that particular sequence.

BRIEF REVIEW OF CONTINUOUS DENSITY HMM

The discussion in the previous section has considered only when the observations are discrete symbols from a finite alphabet. However, observations are often continuous signals. Although we can convert continuous signal representations into sequence of discrete symbols using vector quantization method, sometimes it is an advantage to use HMMs with continuous observation densities.

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3

DYNAMIC TIME WARPING

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Khairul Nadiah Khalid

INTRODUCTION

Template matching is an alternative to perform speech recognition. However, the template matching encountered problems due to speaking rate variability, in which there exist timing differences between the two utterances. Speech has a constantly changing signal, thus it is almost impossible to get the same signal for two same utterances. The problem of time differences can be solved through DTW algorithm: warping the template with the test utterance based on their similarities. So, DTW algorithm actually is a procedure, which combines both warping and distance measurement. DTW is considered as one effective method in speech pattern recognition, however the bad side of this method is that it requires a long processing time plus large storage capacity, especially for real time recognitions. Thus, it is only suitable for application with isolated words, small vocabularies, and speaker dependent with/without multi-speaker, which has yielded a good recognition under these circumstances (Liu, *et al.*, 1992).

Human speeches are never at the same uniform rate and there is a need to align the features of the test utterance before computing a match score. Dynamic Time Warping (DTW), which is a Dynamic Programming technique, is widely used for solving time-alignment problems.

DYNAMIC TIME WARPING

In order to understand Dynamic Time Warping, two procedures need to be dealt with. The first one is the information in each signal that has to be presented in some manner, called features. (Rabiner and Juang, 1993). One of the features is the LPC-based Cepstrum. The LPC-based Cepstrum procedure is the calculation of the distances because some form of metric has to be used in the DTW in order to obtain a match between the database and the test templates. There are two types of distances, which are local distances and global distances. Local distance is a computational different between a feature of one signal and another feature. Global distance is the overall computational difference between an entire signal and another different length signal.

The ideal speech feature extractor might be the one that produces the word that match the meaning of the speech. However, the method to extract optimal feature from the speech signal is not trivial. Thus separating the feature extraction process from the pattern recognition process is a sensible thing to do, since it enables the researchers to encapsulate the pattern recognition process according to (Rabiner and Juang, 1993).

Feature extraction process outputs a feature vector at every regular interval. For example, if an MFCC analysis is performed, then the feature vector consists of the Mel-Frequency Cepstral Coefficients over every fixed tempo. For a LPC analysis the feature vector consists of prediction coefficients while the LPC-based Cepstrum analysis outputs Cepstrum coefficients.

Because the feature vectors could have multiple elements, a method of calculating local distances is needed. The distance measure between two feature vectors can be calculated using the Euclidean distance metric. (Rabiner and Juang, 1993) Therefore, the local distance between two feature vectors x and y is given by,

$$d(x,y)=\sqrt{\sum_{j=1}^{P}(x_j-y_j)^2} \tag{3.9}$$

Although the Euclidean metric is computationally more expensive than some other metrics, it gives more weight to large differences in a single feature.

For example, let consider two feature vectors $A = a_1, a_2, a_3, ..., a_i, ..., a_I$ and $B = b_1, b_2, b_3, ..., b_j, ..., b_J$, let *A* be the template/reference speech pattern while *B* be the unknown/test speech pattern. Translating sequences *A* and *B* into Fig. 3.1, the warping function at each point is calculated. Calculation is done based on Euclidean distance measure as a mean of recognition mechanism. It takes the smallest distance between the test utterance and the templates as the best match. For each point, the distance called local distance, *d* is calculated by taking the difference between two feature-vectors a_i and b_j:

$$d(i, j) = \left\| b_j - a_i \right\| \tag{3.2}$$

Every frame in a template and test speech pattern must be used in the matching path. If a point (*i,j*) is taken, in which *i* refers to the template pattern axis (x-axis), while *j* refers to the test pattern axis (y-axis), a new path must continue from previous point with a lowest distance path, which is from point (*i-1, j-1*), (*i-1, j*), or (*i, j-1*) of warping path shown in Fig. 3.2.

If *D(i,j)* is the global distance up to (*i,j*) with a local distance at (*i,j*) given as *d(i,j)*, then

$$D(i,j) = min[D(i-1,j-1), D(i-1,j), D(i,j-1)] + d(i,j) \tag{3.3}$$

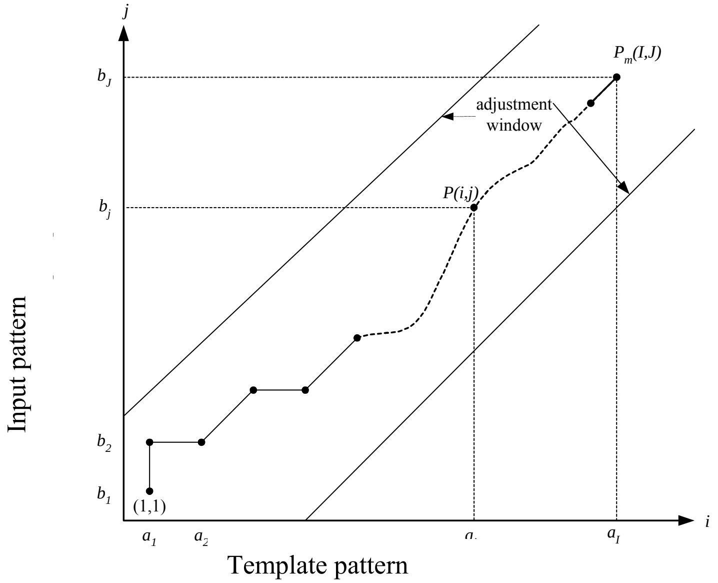

Fig. 3.1 Fundamental of warping function

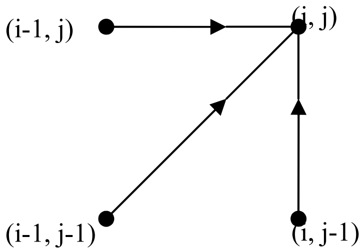

Fig. 3.2 DTW heuristic path type 1

Back to reference pattern *A* and *B*, if their feature vector *B* and an input pattern with feature vector *A*, which each has N_A and N_B frames, the DTW is able to find a function $j=w(i)$, which maps the time axis *i* of *A* with the time axis *j* of *B*. The search is done frame by frame through *A* to find the best frame in *B*, by making comparison of their distances. After the warping function is applied to *A*, distance *d(i,j)* becomes

$$d(i,j(i)) = \left\| b_j' - a_i \right\| \tag{3.4}$$

Then, distances of the vectors are summed on the warping function. The weighted summation, *E* is:

$$E(F) = \sum_{i=1}^{I} d(i,j(i)) * w(i) \tag{3.5}$$

where *w(i)* is a nonnegative weighting coefficient. The minimum value of *E* will be reached when the warping function optimally aligned the two pattern vectors.

A few restrictions have to be applied to the warping function to ensure close approximation of properties of actual time axis variations. This is to preserve essential features of the speech pattern. Rabiner and Juang (1993) outlined the warping properties as follows for DTW path Type I:

1. Monotonic conditions imposed: $j(i-1) \le j(i)$
2. Continuity conditions imposed: $j(i) - j(i-1) \le 1$
3. Boundary conditions imposed: $j(i) = 1$ and $j(J) = I$
4. Adjustment window implementation: $\left| i - j(i) \right| \le r$, r is a positive integer
5. Slope condition: to hold this condition, say if $b'_{j(i)}$ moves forward in one direction *m* times consecutively, then it must also step *n* times diagonally in that direction. This is to make sure a realistic relation between *A* and *B*, in which short

segments will not be mapped to longer segments of the other. The slope is measured as: $M = \frac{n}{m}$.

The warping function slope is more rigidly restricted by increasing *M*, but if slope is too severe then time normalization is not effective, so a denominator to time normalized distance, *N* is introduced, however it is independent of the warping function.

$$N = \sum_{i=1}^{I} w(i) \tag{3.6}$$

So, the time normalized distant becomes

$$D(A,B) = \frac{1}{N} \underset{F}{Min} \left[\frac{\sum_{i=1}^{I} d(i,j(i)) * w(i)}{\sum_{i=1}^{I} w(i)} \right] \tag{3.7}$$

Having this time normalized distant, minimization can be achieved by dynamic programming principles.

There are two typical weighting coefficients that permit the minimization (Rabiner and Juang, 1993):

1. ***Symmetric time warping***
   The summation of distances is carried out along a temporary defined time axis $l=i+j$.
2. ***Asymmetric time warping***
   Previous discussion has described the asymmetric type, in which the summation is carried out along i axis warping *B* to be of the same size as *A*. The weighting coefficient for asymmetric time warping is defined as:

$$w(i) = j(i) - j(i-1) \tag{3.8}$$

When the warping function attempts to step in the direction of the j axis, the weighting coefficient is reduce to 0 because $j(i) = j(i-1)$, thus $w(i) = 0$. Meanwhile, when the warping function steps in the direction of i axis or diagonal, then $w(i) = 1$, so $N = I$.

The asymmetric time warping algorithm only provides compression of speech patterns. Therefore, in order to perform speech pattern expansion, a linear algorithm has to be employed.

SYMMETRICAL DTW ALGORITHM

In speech signal, different speeches have different durations. Ideally, when comparing different length of utterances of the same word, the speaking rate and the utterance duration should not contribute to the dissimilarity measurement. Several utterances of the same word are possibly to have different durations while utterances with the same duration differ in the middle because different parts of the words have been spoken in different rates. Thus a time alignment must be done in order to get the global distance between two speech patterns.

This problem is illustrated in Fig. 3.3, in which a “time to time” matrix is used to visualize the alignment. The reference pattern goes up the side and the input pattern goes along the bottom. As shown in Fig. 3.3, “KOSsONGg” is the noisy version of the template “KOSONG”. The idea is ‘s’ is closer match to “S” compared with other alphabets in the template. The noisy input is matched against all the templates. The best matching template is the one that has the lowest distance path aligning the input pattern to template. A simple global distance score for a path is simply the sum of local distances that make up the path.

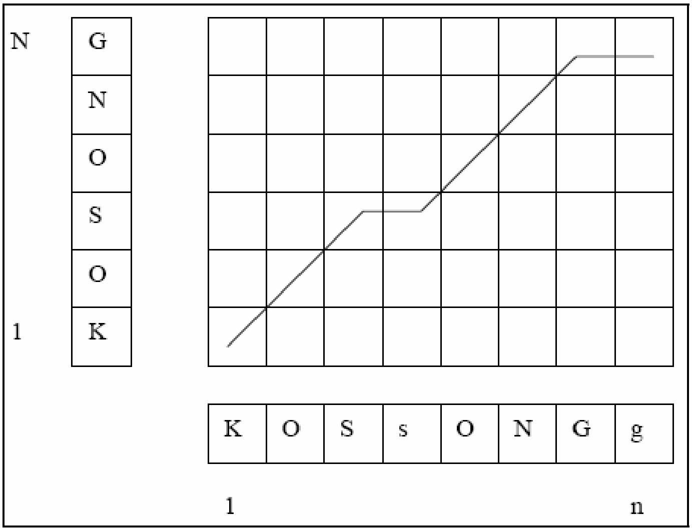

Fig. 3.3 Illustration of time alignment between pattern “KOSONG” and a noisy input “KOSsONGg”

Now the lowest global distance path (or the best matching) between an input and a template can be evaluated by all possible paths. However, this is very inefficient as the possible number of path increases exponentially as the input length increases. So some constraints have to be considered on the matching process and using these constraints as efficient algorithm.

There are many types of local constraints imposed, but they are very straightforward and not restrictive. The constraints are:

1) Matching path cannot go backwards in time.
2) Every frame in the input must be used in a matching path.
3) Local distance scores are combined and added to give a global distance.

For now every frame in the template and input must be used in a matching path. If a point (i,j) is taken in the time-time matrix(where i indexes the input pattern frame, j indexes the template frame), then previous point must be (i-1,j-1), (i-1,j) or (i,j-1). The key idea in this dynamic programming is that at point (i,j) we can only continue from the lowest distance path that is from (i-1,j-1),(i-1,j) or (i,j-1).

If D(i,j) is the global distance up to (i,j) and the local distance at (i,j) is given by d(i,j), thus,

$$D(i,j) = \min[D(i-1,j-1), D(i-1,j), D(i,j-1)] + d(i,j) \qquad (3.10)$$

Given that D(1,1)=d(1,1), the efficient recursive formula for computing D(i,j) can be found (Rabiner and Juang, 1993). The final global distance D(n, N) is the overall score of the template and the input. Thus, the input word can be recognized as the word corresponding to the template with the lowest matching score. The N value is normally different for every template.

The symmetrical DTW requires very small memory because the only storage required is an array that holds every column of the time-time matrix. The only direction that the match path can move when at (i,j) in the time-time matrix are as shown in Fig. 3.4.

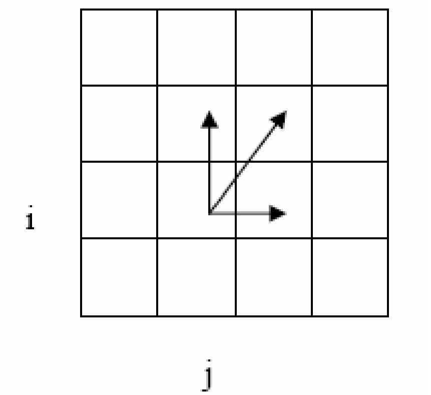

Fig. 3.4 The three possible directions the best matched may move

IMPLEMENTATION DETAILS

The pseudo code for calculating the least global cost (Rabiner and Juang, 1993) is:

```
calculate first column (predCol)
for i=1 to number of input feature vector
    curCol[0]=local cost at (i,0) + global cost at (i-1,0)
    for j=1 to number of template feature vectors
        curCol[j]=local cost at (i,j)+minimum of global
            costs at (i-1,j),(i-1,j-1) or (i,j-1)
    end for j
    predCol=curCol
end for i
minimum global cost is value in curCol[number of templater
feature vectors]
```

VARIOUS LOCAL CONSTRAINTS

Although the Symmetrical DTW algorithm has benefit of symmetry, this has the side effect of penalizing horizontal and vertical transitions compared to the diagonal ones (Rabiner and Juang, 1993). To ensure proper time alignment while keeping any potential loss of information to a minimum, the local continuity constraints need to be added to the warping function. The local constraints can have many forms. According to Rabiner and Juang (1993), the local constraints are based on heuristics. The speaking rate and the temporal variation in speech utterances are difficult to model. Therefore the significance of these local constraints in speech pattern comparison cannot be assessed analytically. Only the experimental results can be used to determine their utility in various applications.

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4

DYNAMIC TIME WARPING FRAME FIXING

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INTRODUCTION

Feature extraction is a vital part in speech recognition process without good and appropriate feature extraction technique, a good recognition cannot be expected. In this chapter, Dynamic Time Warping Fixed Frame (DTW-FF) feature extraction technique is presented. Further processing using DTW-FF algorithm to extract another form of coefficients is also described in which these coefficients will be used in the speech recognition stage. Also included in this chapter is example of some results using the DTW-FF method followed by the discussion.

DTW FRAME FIXING

In general, DTW frame fixing/alignment or DTW fix-frame algorithm (DTW-FF) is done by matching the reference frames against input frames with an emphasis on limiting the input frames to the same number of reference frames. The algorithm is composed based on compression and expansion technique. The frame compression is done when several frames of unknown input are matched to a single frame of reference template. On the other hand, expansion is done when a single unknown input frame is matched with few frames of the reference. Calculation is done based on Euclidean distance measure as a mean of recognition method. This means the lowest distance between a test utterance and reference templates will have the best match. For each point, the distance called as local distance, *d* is calculated by taking the difference between two set of feature-vectors a_i and b_j (refer to Chapter 3).

Every frame in the template and test speech pattern must be used in the matching path. Considering DTW type 1 (which is the type used in the experiment), if a point *(i,j)* is taken, in which *i* refers to the test pattern axis (x-axis), while *j* refers to the template pattern axis (y-axis), a new path must continue from previous point with a lowest distance path, which is from point (*i-1, j-1*), (*i-1, j*), or (*i, j-1*). Given a reference template with feature vector *R* and an input pattern with feature vector *T*, each has N_T and N_R frames, the DTW is able to find a function *j=w(i)*, which maps the time axis *i* of *T* with the time axis *j* of *R*. The search is done frame by frame through *T* to find the best frame in *R*, by making comparison of their distances.

Template matching is an alternative to perform speech recognition beside other methods like linear time normalization, vector quantization or even HMM. The template matching encountered problems due to speaking rate variability, in which there exist timing differences between the similar utterances. However, time normalization has to be done prior to the template matching found in Uma *et al. (*1992), Sae-Tang and Tanprasert (2000), and Abdulla *et al.* (2003). Dynamic Time Warping (DTW) method was first introduced by Sakoe and Chiba (1978), in which it was used for recognition of isolated words in association with Dynamic Programming (DP). Uma *et al.* (1992) used a collection of reference pattern compared against the test pattern based on the word patterns collected from different speakers. They did not use the window and slope constraints found in Sakoe and Chiba (1978).

The problem of time differences can be solved through DTW algorithm, which is by warping the reference template against the test utterance based on their features similarities. So, DTW algorithm actually is a procedure that combines both warping and distance measurement, which is based on their local and global distance. In this research context, local distance is the distance between the input data and the reference data for respective vectors along the speech frames.

In this research, the time normalization is done based on DTW method by warping the input vectors with a reference vector which has almost similar local distance. It was done by expanding vectors of an input to reference vectors which shows a vertical movement: it shares the same feature vectors for a feature vector frame of an unknown input. This frame alignment is also known as the expansion and compression method, this is done following the slope conditions described as follows. There are three slope conditions that have to be dealt with in this research work, based on the DTW Type 1 (refer to Fig. 3.1):

i- Slope is 0 (horizontal line)

When the warping path moves horizontally, the frames of the speech signal are compressed. The compression is done by taking the minimum calculated local distance amongst the distance set, i.e. compare *w(i)* with *w(i-1), w(i+1)* and so on, and choose the frame with minimum local distance.

ii- Slope is ∞ (vertical line)

When the warping path moves vertically, the frame of the speech signal is expanded. This time the reference frame gets the identical frame as *w(i)* of the unknown input source. In other words, the reference frame duplicates the local distance of that particular vertical warping frame.

iii- Slope is 1 (diagonal)
When the warping path moves diagonally, the frame is left as it is because it already has the least local distance compared to other movements.

Examples of the slope conditions are shown in Fig. 4.1.

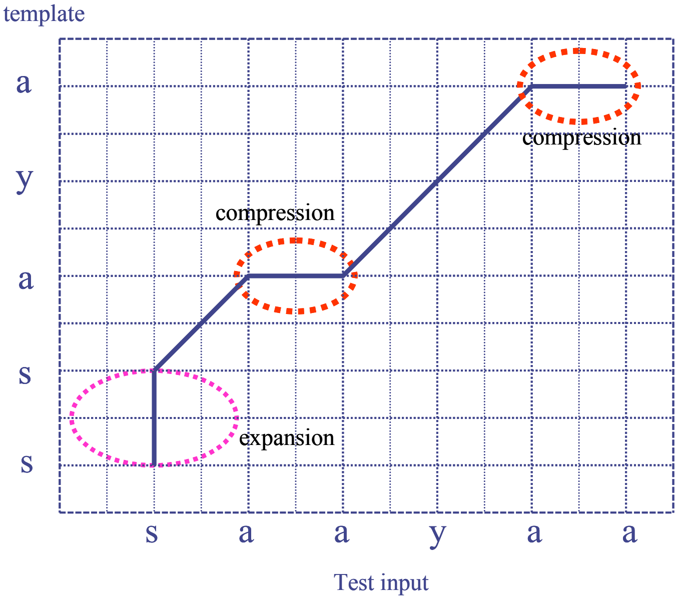

Fig. 4.1 Compression and expansion rules

The ***F***$^{-}$ and ***F***$^{+}$ is done by using our new so called DTW frame fixing algorithm (DTW-FF). Consider the frame vectors of LPC coefficients for input as *i,…I*, and reference as *j…J*, while *F* denotes the frame. Frame compression involves searching minimum local distance out of distances in a frame set within a threshold value represented as

$$F^{-} = F(min\{d_{(i,j)\ldots(I,J)}\}) \qquad (4.1)$$

For example, if a horizontal warping path moved three frames in a row, compression will take place. As stated in the Slope Condition 1, only one frame that has the least distance from it previous point is selected to represent the DTW-FF coefficient.

Frame expansion involves duplicating a particular input frame to multiple reference frames of *w(i)*, represented as

$$F^{+} = F(w(i)) \tag{4.2}$$

The duplicated frames are the expanded frames resulted from the vertical warping path. The normalized data/sample has been tested and compared to the typical DTW algorithm and results showed the same global distance score.

RESULTS OF DTW-FF ALGORITHM

The normalized data/sample has been tested and compared to the typical DTW algorithm and results showed the same global distance score. As a preliminary example to the DTW-FF algorithm, Fig. 4.2 and Fig. 4.3 showed the comparison between using the typical DTW and DTW-FF algorithm. It is clearly shown that the input template has 39 frames (0-38) and the reference template has 35 frames (0-34) and the warping path showed the same score of 48.34.

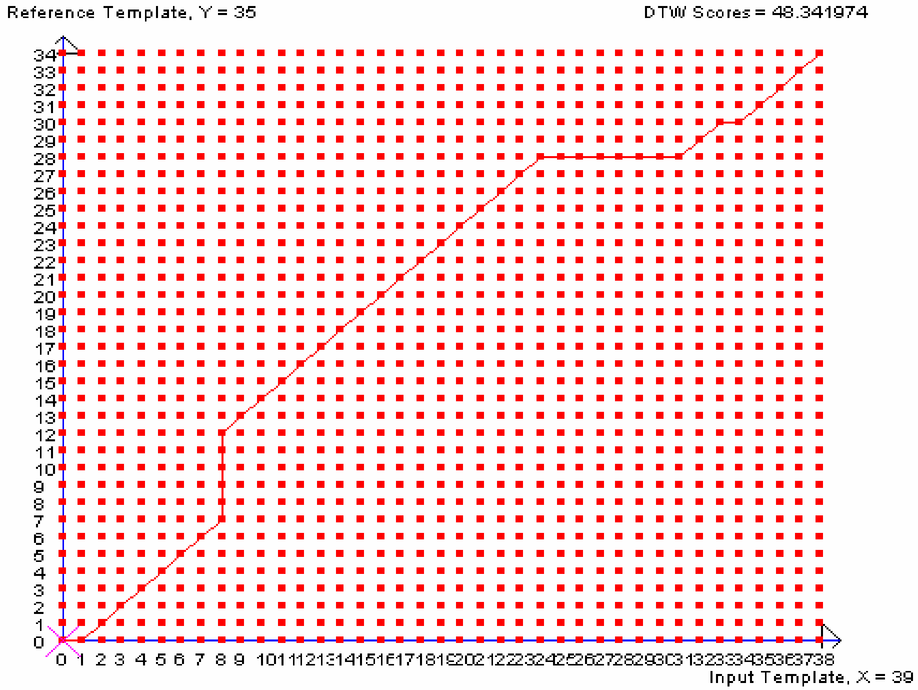

Fig. 4.2 A warping path of word ‘dua’ generated from typical DTW algorithm

However, it can be observed in Fig. 4.3 that expansion takes place in frame 8 of the input template, being expanded to 6 frames (refer to the y-axis which shows the frame expansion). Meanwhile, compression occurs in frame 24 through 31 of the input template whereby these frames are compressed to one frame only. This is because the local distances between the frames are almost similar, but it still considers the frame with least distance to represent those frames in the warping path coordinates. Other compressions occur in frame 0 and 1 as well as in frame 34 and 35 of the input signal, both are compressed to one frame. Finally, the DTW-FF algorithm was able to fix the test signal frame number equal to the reference signal frame.

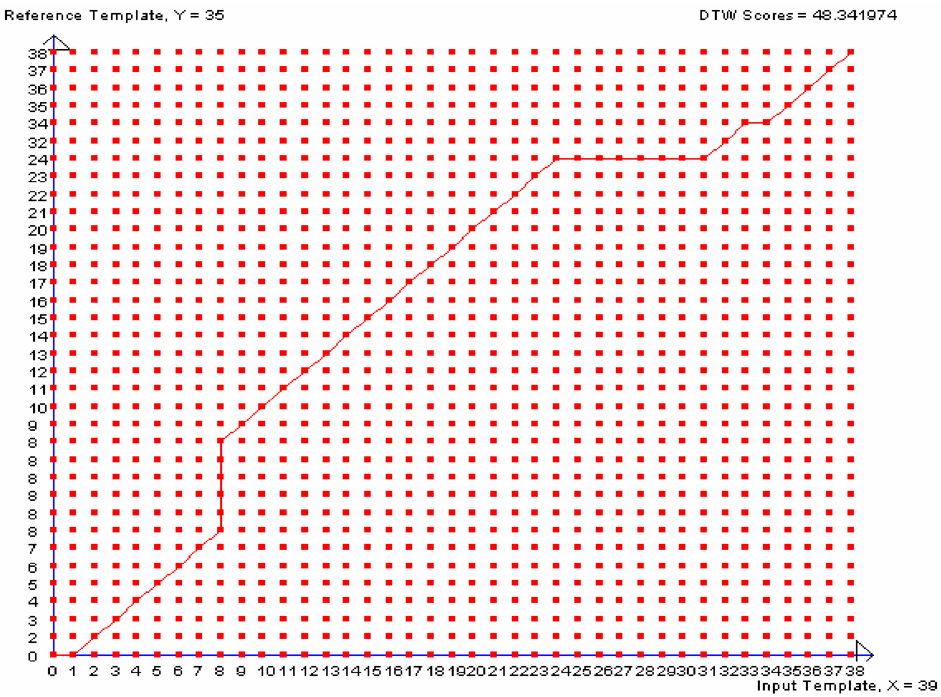

Fig. 4.3 A warping path generated from the DTW-FF algorithm showing the expansion and compression of frames

Fig. 4.4 shows an input with the frames that has been matched to a reference template of the same utterance (word 'kosong'). In this example, initially the input template has 38 frames while the reference template has 42 frames. By using the DTW-FF algorithm the input frames have been expanded to 42, i.e. equals to the number of frames of the reference template following the slope conditions outlined earlier in this chapter. Let w(y) as the input frame and r(x) as the reference frame.

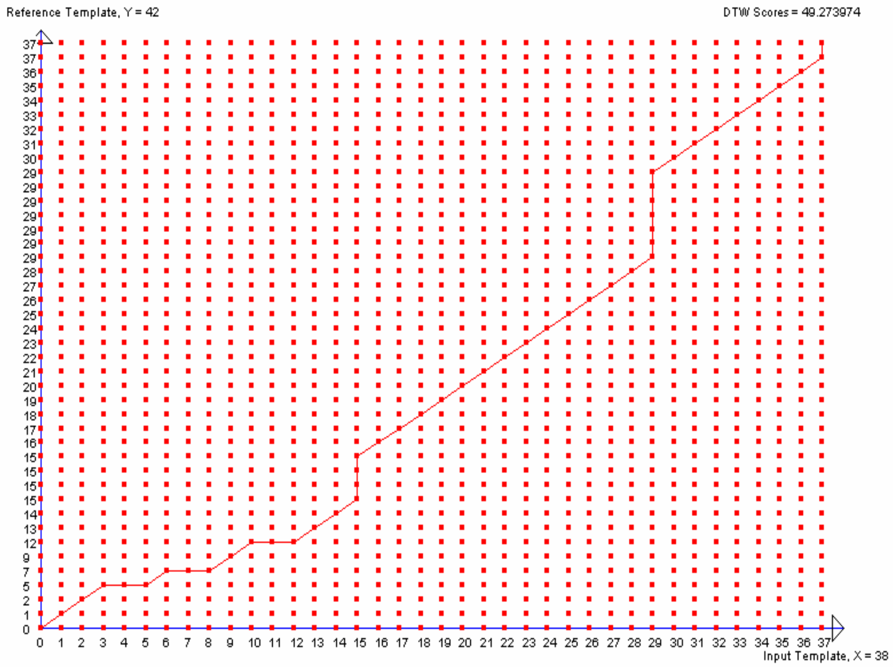

Fig. 4.4 The DTW frame alignment between an input and a reference template; the input which initially has 38 frames is fixed to 42 frames.

According to the slope condition (i), the local distances of the unknown input frames of w(3),…, w(5)[1] are compared and w(5) appears to have the minimum local distance among these three frames, so those 3 frames are compressed to one and occupies only frame r(4). The same goes with frame w(6),…, w(8) in which frame w(7) has the least local distance with respect to the reference template, so they are compressed and occupies only frame r(5).

On the other hand, slope condition (ii) provides an expansion to the input frame. For example, while frame w(15) of the input is

[1] *w* represents the frame of the unknown input frames (in x-axis) while *r* represents the reference template frame (in y-axis).

expanded to 4 frames, in which these 4 consecutive frames in the reference template are identical; i.e. 4 frames of reference template at frame r(10),…, r(13) have the same feature vectors as frame w(15) of the input vectors, so frame w(15) occupies frame r(10),…, r(13). These mean that frame w(15) of the input has matched 4 feature vectors in a row of the reference template set.

Since the diagonal movement (slope condition (iii)) is the fastest track (shortest path) towards achieving the global distance point and giving the least local distance at all time compared to the horizontal or vertical movements, no changes is made to the frames involved, thus this slope considers a normal DTW procedure. A closer view of the frame fixing between frame 4 and 16 in Fig. 4.4 can be viewed in Fig. 4.5.

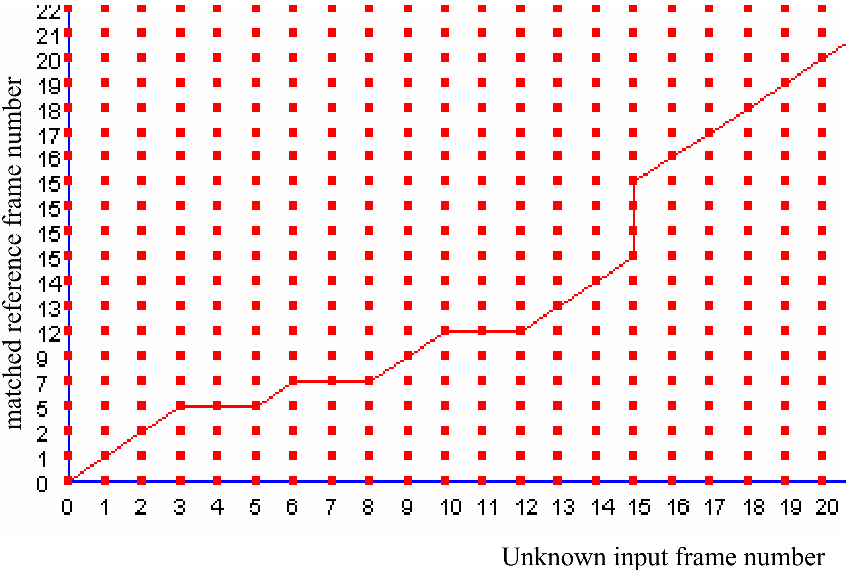

Fig. 4.5 A close-up view of Fig. 4.8 to show the compression and expansion of template frames activities between frame 4 and frame 16

To further understand the frame fixing, let's consider other examples. Figure 4.6 and Figure 4.7 show the input template frames that are being fixed to a fix number of frames according to the reference template frames. In this particular word example, which is 'carry' extracted from the TIMIT database. Initially the input template has 24 and 32 frames for Subject A and B respectively, where the reference template has 27 frames. By using the DTW-FF algorithm, the input frames have been expanded from 24 to 27 for Subject A. However, compression occurred in Subject B, from 32 frames to 27 frames, i.e. equals to the number of frames in reference template.

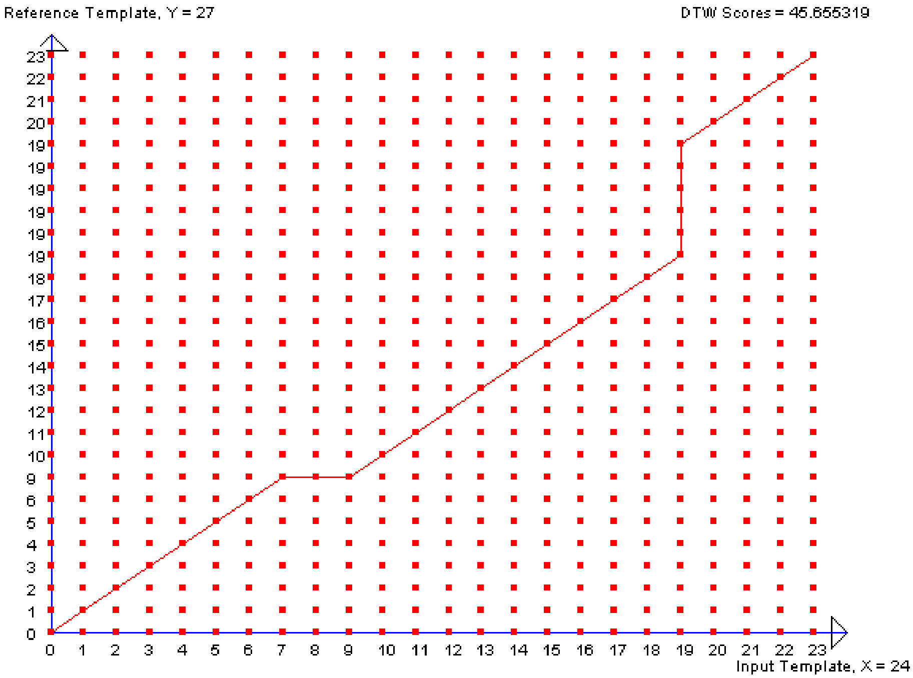

Fig. 4.6 The DTW frame fixing between an input and a reference template for word 'carry' of a subject (Subject A).

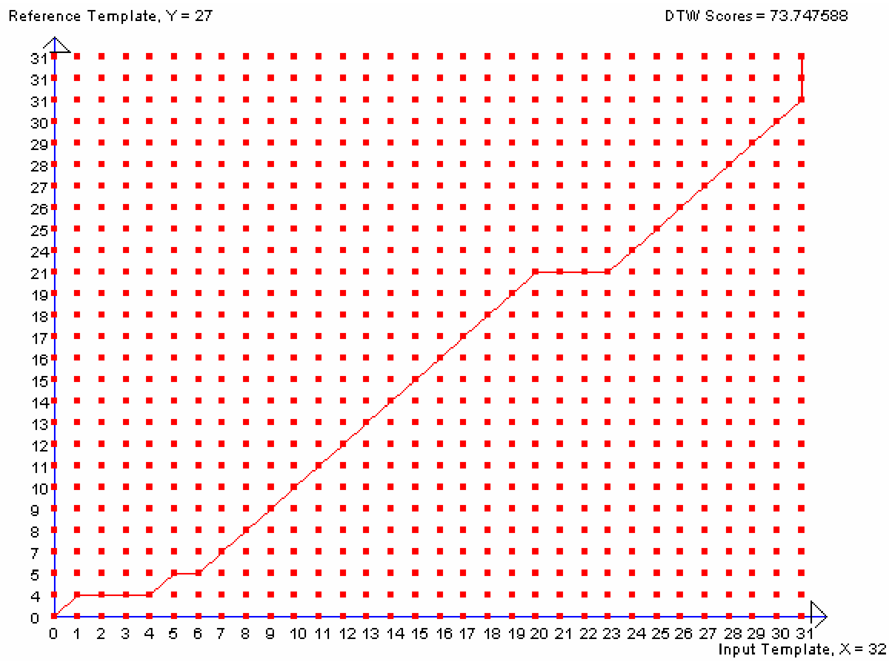

Fig.4.7 The DTW frame fixing between an input and a reference template for word ‘carry’ of another subject (Subject B)

In Fig. 4.7, frame compression is performed in frames r(7), r(8), and r(9), and r(9) has the least local distance score (as indicated on the reference template axis), thus loosing 2 frames here. On the other hand, frame 19 is expanded to 6 frames, but considered as gaining 5 frames, so the final number of frames after the fixing process is equal to 24-2+5 = 27 frames.

Meanwhile in Fig. 4.8, frames r(1), r(2), r(3), and r(4) are compressed to 1 (selecting r(4) which has the least local distance score among the frames), thus loosing 3 frames. For frames r(5) and r(6), the frames are compressed and frame 5 is selected because of its lesser distance score than frame 6, thus losing by 1 frame, and the same goes to frame 20, 21, 22, and 23, they are compressed and represented by frame 21, this time they are losing 3 frames. But frame 31 is expanded to 3 frames, means that it gains 2 more frames in this expansion process. Therefore, after frame fixing the total number of frames is equal to 32-3-1-3+2 = 27 frames.

DTW-FF features are obtained from the matching process in the DTW-FF algorithm. The scores have been reduced from LPC coefficient which is a 10-order feature vectors, into a coefficient (which is called as DTW-FF coefficient) derived from each frame. Besides fixing to equal number of frames between the unknown input and the reference template, this activity has also tremendously reduced the amount of inputs presented into the back-propagation neural networks. As an example, calculation to show the input size reduction for 250 samples of 49 frames with LPC order-10 is as follows:

For input using the LPC coefficients,

$$\begin{aligned}\text{Input}_{\text{LPC}} &= \#\text{ of utterance} \times \#\text{ of frames/utterance} \\ &\quad \times \#\text{ of coefficient/frame} \qquad (4.1)\\ &= 250\text{ utterances} \times 49\text{ frames/utterance} \\ &\quad \times 10\text{ coefficient/frame} \\ &= 122{,}500\text{ input coefficients}\end{aligned}$$

For input using the local distance score,

$$\begin{aligned}\text{Input}_{\text{LD}} &= \#\text{ of utterance} \times \#\text{ of frames/utterance} \\ &\quad \times\ \text{number of coefficient/frame} \\ &= 250\text{ utterances} \times 49\text{ frames/utterance} \\ &\quad \times 1\text{ coefficient/frame} \\ &= 12{,}250\text{ input coefficients}\end{aligned}$$

Therefore, the percentage of number coefficients reduced is

$$\text{\# of coefficients reduced (\%)} = \frac{\text{Input}_{\text{LPC}} - \text{Input}_{\text{LD}}}{\text{Input}_{\text{LPC}}} \text{x}100\%$$

$$= \frac{122500 - 12250}{122500} \text{x}100\%$$
$$= 90\ \%$$

Remember that the number of inputs to the back-propagation neural networks has been reduced by 90% using the local distance scores instead of the LPC coefficients, and still been able to yield to a high recognition rate. The reduced coefficients percentage will be higher if higher LPC order was used.

For example, if LPC of order 12 is used, then:

$\text{Input}_{\text{LPC}}$ = 250 utterances × 49 frames/utterance
× 12 coefficient/frame
= 147,000 input coefficients

Input using local distance score,

Input_{LD} = 250 utterances × 49 frames/utterance
× 1 coefficient/frame
= 12250 input coefficients

Therefore, the percentage of number coefficients reduced is

Number of coefficients reduced (%) = 91.7%

These means a lot of network complexities and amount of connection weights computations during the forward pass and backward pass can be reduced. Thus a faster convergence is achieved (also means less computation time) and this also allows more parallel computing of the speech patterns being done at a time (more patterns can be fed into the neural networks at the same time).

From the observation of the experiment, the number of the frames after being fixed, N_{ff} is formulated as

$$N_{ff} = N_{if} - N_{cf} + N_{ef} \tag{4.4}$$

where N_{if} number of input frame

N_{cf} number of compressed frame

N_{ef} number of expanded frame

Having done the expansion and compression along the matching path, the unknown input frame is matched to the reference template frames. The frame fixing/ matching is a mean of solution to speech frame variations whereby this technique still preserved the global distance score as in the typical DTW method; the DTW fixing frame (DTW-FF) algorithm only make adjustment on the feature vectors of the horizontal and vertical local distance movements, leaving the diagonal movements as it is with their respective reference vectors. The frame fixing is done throughout the samples, also taking considerations to the sample which has the same number of frames as the averaged frames as the reference template.

In comparison, the LTN technique (Salleh, 1997) used a procedure of omitting and repeating the frames to normalize the variable length of speech sample with a fixed number of parameters. In the study the fixed parameter is the reference template's frame number, so the frame number is fixed to a desired length suitable with the overall samples. However, LTN technique looses some information during the normalization process: the experiment conducted led to 13-22% equal error rate throughout the samples tested, which is considered as quite high. This was due to the omission and repetition of unnecessary information into the speech frame (in order to fixed the frame numbers) whereby this is seen as a disadvantage of using the LTN technique for time normalization. Nevertheless, the DTW-FF technique proposed in this study does not lose any information during the time alignment process. Based on the counter-check experiment carried out between the LPC coefficients and the derived DTW-FF coefficients using the traditional DTW recognition engine, the recognition accuracy is the same and this gives some indications that the information in the speech samples remained.

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5

PITCH SCALE HARMONIC FILTER

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Muhd Noorul Anam Mohd Norddin

INTRODUCTION

Pitch is defined as the property of sound that varies with variation in the frequency of vibration. In speech processing aspect, pitch is defined as the fundamental frequency (oscillation frequency) of the glottal oscillation (vibration of the vocal folds). Pitch information is one of speech acoustical features that not often taken into consideration while doing speech recognition. In this research, pitch is taken into consideration then it is optimized and was used as another feature into NN along with DTW-FF feature. Pitch contains spectral information of a particular speech, it is the feature that was used to determine the fundamental frequency, *F0* of a speech at a particular time.

PITCH FEATURE EXTRACTION

The pitch feature considered in the study is extracted using a method called pitch scaled harmonic filter (PSHF) (Jackson and Mareno, 2003). In PSHF, pitch is optimized and these pitch feature is retained and used as another input feature which is combined with the DTW-FF feature for recognition using the NN. These pitch features represent the formant frequencies of spoken utterance. The optimization is needed in order to resolve glitches due to octave error during the spectral activities, especially when there is noise signal during the recording of the speech sample.

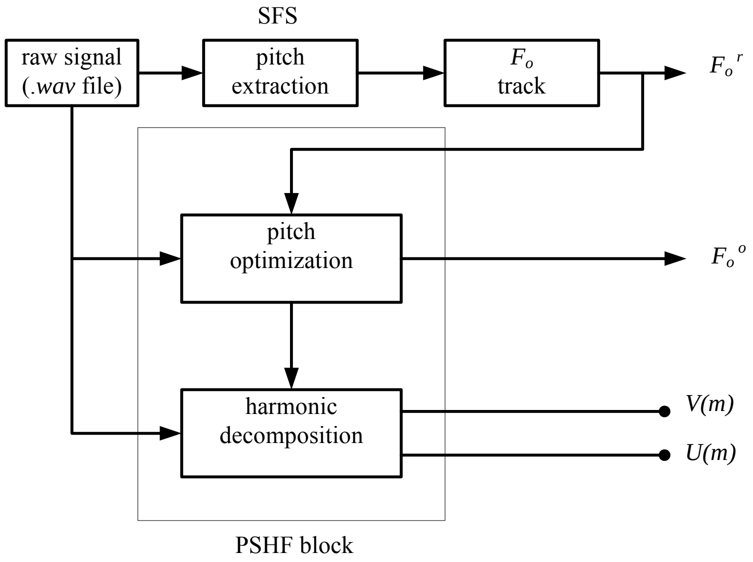

Fig. 5.4 Process flow of pitch optimization (Adapted from Jackson and Mareno, 2003).

Fig. 5.4 shows a flow diagram of the pitch optimization process. In short, firstly pitch extraction is done to sampled speech which is in .*wav* format to obtain the initial (raw) values of their fundamental frequencies, or referred as $F_o^{\,r}$; the value can be obtained by pitch-tracking manually or by using available speech-related applications. Then this $F_o^{\,r}$ is fed into the pitch optimization algorithm, to yield an optimized pitch frequency, $F_o^{\,o}$.

Pitch information is one of speech acoustical features that is rarely taken into consideration when doing speech recognition. But pitch is an important feature in the study of speech accents

(Chan *et al.*, 1994; Wong and Siu, 2002). In this research, pitch is optimized and been used as another feature into NN along with LPC feature. Pitch contains spectral information of a particular speech and this is the feature that is being used to determine the fundamental frequency, *F0*. Pitch also affects the estimation of spectral envelopes which the standard feature are sensitive to these pitch changes (Stephenson *et al.*, 2004). With that reason, in this study pitch is optimized so that any pitch degradation could be possibly minimized.

Pitch optimization is performed to resolve glitches in voice activity and pitch discontinuities due to octave errors. The algorithm of the pitch optimization is described in detail in Jackson and Shadle (2001). The pitch tracking algorithm is to estimate the pitch period τ by sharpening the spectrum at the first *H* harmonics, $h \in \{1,2,3,..., H\}$. The lower and higher spectral spreads, S_h^+ and S_h^- described the sharpness of the spectrum. Their spectral equations are (Jackson and Shadle, 2001):

$$S_h^+(m,p) = |S_w(4h+1)|^2 - \frac{|S_w(4h)|^2}{|W(h\Delta f_0)|^2} \left| W\left(h\Delta f_0 - \frac{1}{M}\right)\right|^2 \tag{5.1}$$

$$S_h^-(m,p) = |S_w(4h-1)|^2 - \frac{|S_w(4h)|^2}{|W(h\Delta f_0)|^2} \left| W\left(h\Delta f_0 + \frac{1}{M}\right)\right|^2 \tag{5.2}$$

where $\Delta f_0 = \frac{1}{\Delta\tau} = \frac{4f_s}{\Delta M}$, *M* is the window length, f_s is the sampling frequency, *p* is the increment time and *m* is the sample number. The windowing function used is the Hanning window:

$$W(k) = \frac{M}{2}\left(\text{sinc } \pi kM + \frac{\text{sinc } \pi(kM-1) + \text{sinc } \pi(kM+1)}{2}\right) e^{-j\pi\Delta f_o M} \tag{5.3}$$

The algorithm find the optimum pitch value for a particular time by minimizing the difference between the calculated and the measured smearing of the spectrum due to the window. The difference is calculated by the minimum mean-squared error, according to the cost function for window length, *M*:

$$J(M,p) = \sum_{h=1}^{H} [S_h^{+}(M,p)^2 + S_h^{-}(M,p)^2] \tag{5.4}$$

This cost function is used to match the pitch of the decomposed signals and optimization is done throughout the signal by repeating the process with an increment time *p*. The optimized pitch is compared to other pitch extractor method such as Speech Filing System (SFS) (Huckvale, 2003) to ensure its reliability before they are ready to be fed into NN. The sampling frequency used in this processing is 16 kHz. The result of pitch optimization in Fig. 5.7 shows a very good estimation in which it differs only by ±1Hz compared to using SFS. This result had been used for speech synthesis and proven giving good result in Jackson and Shadle (2001).

The optimized pitch is compared to other available method such as Speech Filing System (SFS) to ensure its reliability before they are ready to be fed into the NN. The sampling frequency used in this processing is 16 kHz. The result of pitch optimization shows a very good estimation; differ only by ±1Hz from SFS/raw pitch (refer to Fig. 5.5). The non-optimized pitch has slightly lower pitch value.

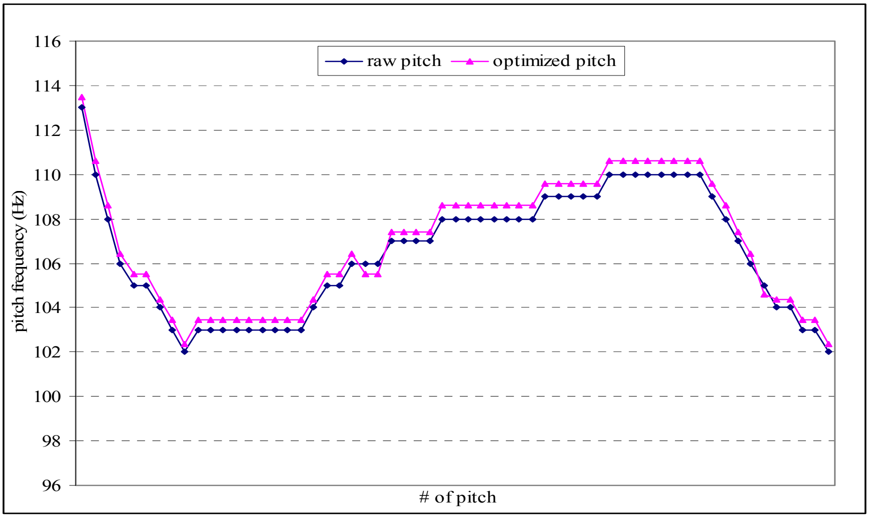

Fig. 5.5 Plot of initial (raw) and optimized pitch of a word. A very small pitch differences are spotted between the extracted pitches.

PITCH FEATURE EXTRACTION SOFTWARE

The extraction of pitch feature using pitch scaled harmonic filter is described in details in this section. The process of selecting the input and output filenames is also presented so that they are organized and stored accordingly in order for easy access since there are many files that will be generated from the PSHF procedure. Some good and bad examples, error messages, level of reporting during the execution, and graph plots from the results are also included for reference while using the software.

The Pitch-Scaled Harmonic Filter (PSHF) is used to decompose the sample speech into two components: (a) voiced and (b) unvoiced components. PSHF V2.00 was the very first version developed by Jackson and Shadle (Jackson and Shadle, 2000). It has been revised several times by Jackson and Mareno (Jackson and Mareno, 2001); the most recent version is V3.10. Currently the PSHF software can be found in Linux and Window versions (refer to web page in citation of Jackson and Mareno, 2001); there has been no manual produced, but some FAQs are posted for references. However, in this section only PSHF Linux version is described.

PSHF Help Menu

Table 5.1 is the PSHF help menu on the default values used for PSHF execution and their explanation.

Table 5.1: PSHF help menu: the default values used and their explanation

Flag	Default	Explanation
-b	[4]	Number of periods used in algorithm
-d	[2]	Initial step size (as a power of 2).
-e	[10.0]	External pitch sampling period (ms).
-i	[10.0]	Internal pitch sampling period (ms).
-m	[40.0]	Minimum fundamental frequency (Hz)
-t	False	Whether fast optimization pitch is performed
-E	[20.0]	External pitch offset (ms).
-H	[8]	Number of periodic in cost function.
-M	[500.0]	Maximum fundamental frequency (Hz).
-P	False	Whether power-based pair are produced
-T	[0]	Different levels of reporting
-S	none	Script of pitch wave files, and output path

The Flags and Options

-b The number of periods used in PSHF algorithm, default is 4. The reason of choosing four-pitch periods is that the periodic part is concentrated into every fourth bin of the spectrum

-d The initial step size is used for setting the processing step

-e External pitch sampling period is the pitch period extracted from the pitch-tracking activity

-i The internal pitch sampling period is the optimized pitch period

-m The minimum fundamental frequency, *F0* can be specified at this option, unless the default value will be used

-t From Table 5.1, "-t" option is self explained

-E This is the point where the external pitch offset can be specified

-H The number of periodic in the cost function

-M Maximum *F0* specification is done at this option. But the default value is high enough for a normal spoken speech, so no need to include this option in the execution line if processing a normal spoken speech signal

-P In this PSHF version, the power-based pair is currently not available. However, this routine will only provide signal-based output

-T Including this option will show the stage of PSHF processing, how many samples has been processed

-S This is a must option because without it nothing will be processed.

HOW TO RUN PSHF

There are some ground rules that has to be followed to run PSHF. The rules are explained in the following subsections.

Pitch-Tracking

The initial values of the fundamental frequency, *F0* that is referred to as the raw pitch, need to be provided before PSHF can be used. The raw pitch estimates can be obtained by pitch-tracking the signal manually, or can be extracted using the shareware software called SFS, which is available from the internet. It can also be extracted from many speech-related applications. The SFS window in Fig. 5.6 show which toolbar is used to extract the raw pitch estimates of the speech signal, while Fig. 5.7 is how the raw pitch estimates being exported to a desired directory; it has to be placed in the same directory as the input waveform. The extracted pitch can be viewed with respect to the source speech as in Fig. 5.8.

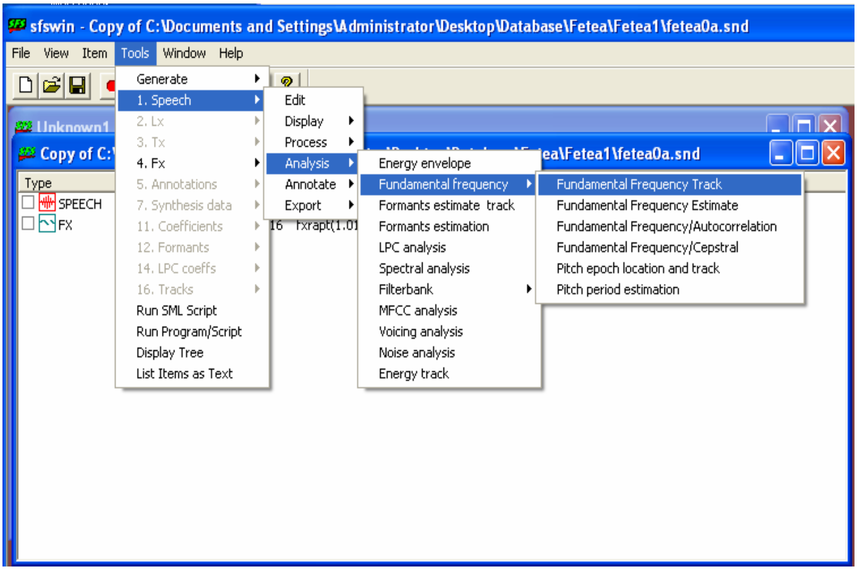

Fig. 5.6 SFS window showing how fundamental frequency pitch track been obtained from the original speech signal.

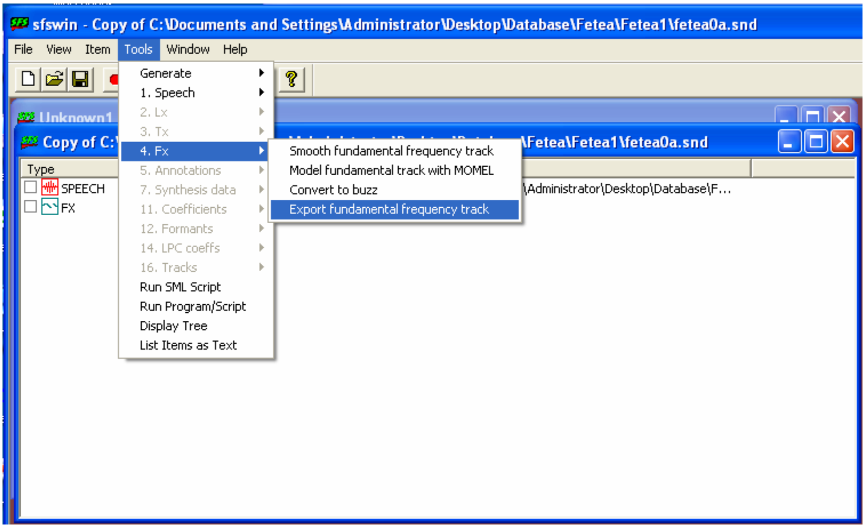
sfswin - Copy of C:\Documents and Settings\Administrator\Desktop\Database\Fetea\Fetea1\fetea0a.snd
File
View
Item
Tools
Window
Help
Unknown1
Copy of C:\
\Fetea\Fetea1\fetea0a.snd
Type
SPEECH
FX
\Administrator\Desktop\Database\F...
Generate
1. Speech
2. Lx
3. Tx
4. Fx
5. Annotations
7. Synthesis data
11. Coefficients
12. Formants
14. LPC coeffs
16. Tracks
Run SML Script
Run Program/Script
Display Tree
List Items as Text
Smooth fundamental frequency track
Model fundamental track with MOMEL
Convert to buzz
Export fundamental frequency track

Fig. 5.7 SFS window showing how extracted fundamental frequency, F_x is exported for PSHF usage.

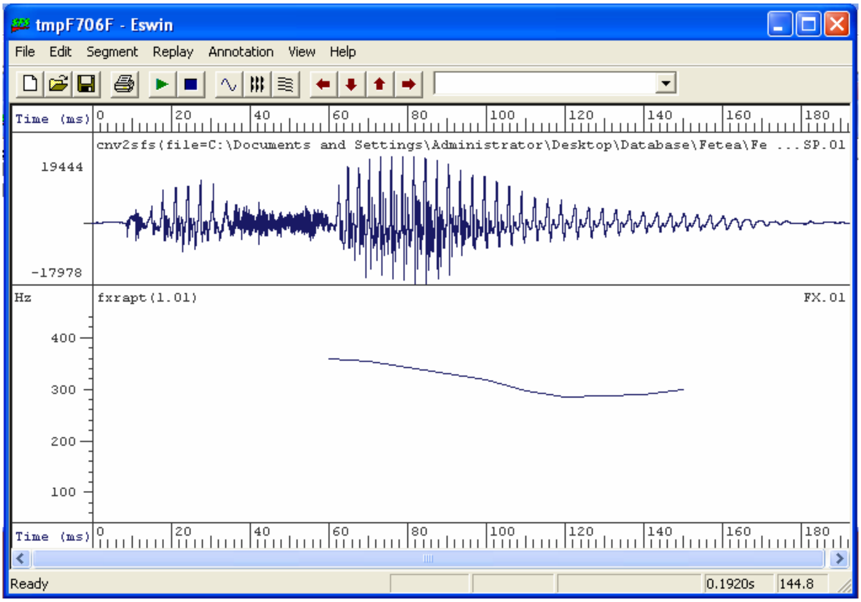

Fig. 5.8 Pitch graphic from SFS; speech signal (top) with corresponding extracted pitch (bottom) on SFS window.

Executing PSHF

To run PSHF, one has to type the following at the command line, which is also already in the run.sh file, in which it is located, in the **\*test*** directory (note that the external pitch estimate could vary from one speech signal to another, so the run.sh file has to be edited accordingly):

```
../pshf -E 8 -e 4 -i 1 -d 1 -S ./scriptfile.scp
```

The external (-e) and internal (-i) sampling rates for the fundamental frequency tracks specify the time between each data point in the raw and optimized pitch tracks, respectively. That is, if there are 530 *F0* values given for a file that is 5.3 seconds in duration, then the external step size is 5.3sec/530 = 10 milliseconds, which would be represented as "-e 10", which corresponds to the spacing between each sample point in the input f0 file. One should know that when running multiple files at once, the "-e" has to has same values, otherwise they have to be executed separately. If the "-e" value is wrong, then a "***segmentation fault***" message will come out and the process ended, so no output will be generated.

Other flags can also be included in the command to view different levels or results status, for example

```
../pshf -E 8 -e 4 -i 1 -d 1 -T 1 -S ./scriptfile.scp
```

to view every step of the reporting levels. Note that by keeping "-i 0" will generate the output pitch track (of the optimized F0 values) for every sample. However, please notice that "-i" can only accept the values 0, 1, and a value equal to the "-e" option. Be warned that choosing "-i 0" will slow down the PSHF execution very much because of a very small offset for each pitch track, yet it returns essentially the same results as "-i 1".

The following is an example of command line, which includes the different level of reporting, ***-T*** option. At the percent sign, write

```
../pshf -E 8 -e 5 -i 5 -d 2 -T 2 -S ./scriptfile.scp
```

and press ‘enter’. Then the following result will be generated.

```
 -- PSHF v3.10 by Philip J.B.  Jackson \& David M.  Moreno, (c)
2003 --

  nT = 65501, nSeg = 34927
  nT = 113963, nSeg = 47337
  nT = 139189, nSeg = 24849
  nT = 252459, nSeg = 73059
  nT = 295903, nSeg = 37219
  nT = 402229, nSeg = 69673
  nT = 441843, nSeg = 40095
 in/fetea1\fetea_0a.wav  out/fetea\fetea_0a

 -------------- PSHF process completed successfully ---------------
```

where nT is number of points in temporary signals and nSeg is number of point in resultant output signals.

Input-Output Files Organization

The input and output filenames should be edited in the scriptfile.scp file using any word editor. The line looks as follows with corresponding raw pitch estimate, the waveform, and base name to use for output files; voiced component(filename ***_v.wav***) and unvoiced component (filename ***_u.wav***) result. The bold italic parts are generated automatically indicating the periodic and aperiodic component respectively.

```
          in/raw\_pitch.f0          in/waveform.wav       out/filename
```

PSHF is capable of running several wave files at a time, but it requires a set of raw pitch estimates (.f0 file) for each wave file along with the input waveform. Nevertheless, one set of input and output does not have to be in the same directory as the other sets. A multiple-wave-files run should be written as follows in the scriptfile.scp file. The scriptfile.scp can be edited using any word editor, i.e.: wordpad, notepad, winedt.

```
in/raw_pitch1.f0      in/waveform1.wav     out/filename1
in1/raw_pitch2.f0     in1/waveform2.wav    out/filename2
in2/raw_pitch3.f0     in2/waveform3.wav    out/filename3
```

Note that the raw pitch fundamental frequency has to be in the same directory as the input waveform, and the output will automatically be generated in the output directory, consisting of two output files: filename_v.wav and filename_u.wav, and an optimized pitch file, filename_opt.f0, is also generated into the output directory. A simple block diagram in Fig. 5.9 summarizes the files required as input for PSHF and the output files generated. If the .f0 file is not in the same directory as the input .wav file, the PSHF will pop a message "***unsuccessful in reading input files***". On the other hand, if the .f0 file is not configured correctly, the "***PitchFile couldn't be opened!***" message will come out.

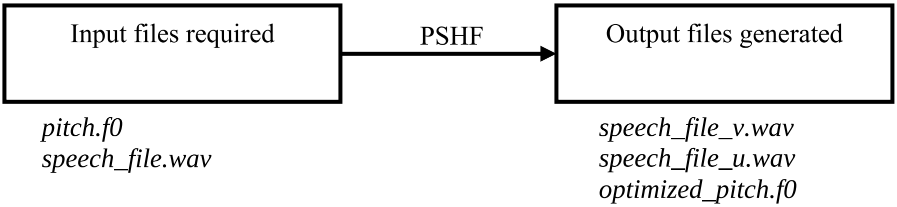

Fig. 5.9 Block diagram to summarize the required input and generated output files in PSHF process

The difference between the estimates of fundamental frequency (raw_pitch.f0) and the optimized frequency (filename_opt.f0) can be seen by plotting the curves from both files, see Fig. 5.10. From the plot, it can be seen that the optimized pitch frequency has a slightly higher value than the estimates.

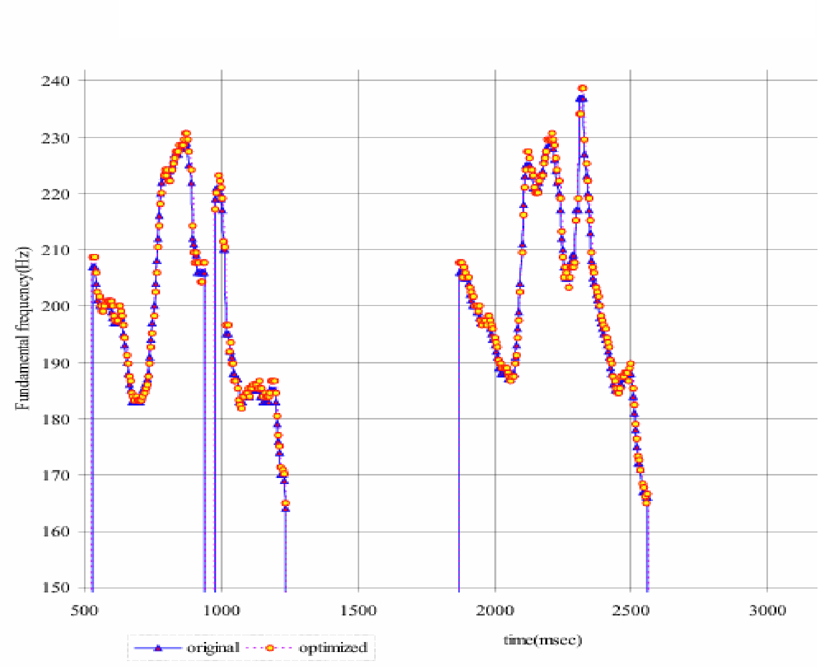

Fig. 5.10 Example of the estimates and optimized fundamental frequency plotted against time in milliseconds.

Example: 'before' and 'after' PSHF

The signals in Figure B.8 are signals before and after going through PSHF algorithm, for a vowel-fricative combination of nonsense word /avaivi/ spoken by an adult female subject. The figure was produced using Matlab with command lines written in M-file shown in Fig. 5.12. Be aware that the M-file and other files used in the routine sit in the same directory, i.e. in this example, the original signal is avaivi.wav while the output files are avaivi_v.wav and avaivi_u.wav.

The command line for this example is:

```
../pshf -E 8 -e 5 -i 5 -d 2 -T 3 -S ./scriptfile.scp
```

and the result is generated as follows:

```
 -- PSHF v3.10 by Philip J.B.  Jackson \& David M.  Moreno, (c)
2003 --
  offset = 17183
  offset = 17423
  nT = 17669, nSeg = 725
  offset = 21023
  offset = 21263
  offset = 21503
  nT = 50165, nSeg = 29599
  offset = 80303
  offset = 80543
  offset = 80783
  nT = 105383, nSeg = 25477
  offset = 136703
  offset = 136943
  offset = 137183
  nT = 163707, nSeg = 27371
  offset = 166703
  offset = 166943
  offset = 167183
  nT = 167391, nSeg = 895
 in/fetea1/fetea0a.wav  out/fetea1/fetea0a

 -------------- PSHF process completed successfully --------------
```

Note: offset is the number of current pitch frames.

```
 % The following command is to call /'kosong'/ from the PSHF
output directory
          original=wavread('kosong.wav');
           voiced=wavread('kosong_v.wav');
           unvoiced=wavread('kosong_u.wav');

          var=0.5;
          nfft=input('nfft = ');
          Fs = 48000;
          window = nfft;
          noverlap = round(window*var);

          [B1,F1,T1]=specgram(original, nfft, Fs, window,
noverlap);
          [B2,F2,T2]=specgram(voiced, nfft, Fs, window, noverlap);
          [B3,F3,T3]=specgram(unvoiced, nfft, Fs, window,
noverlap);

  % Command to convert x-axis from number of samples to time
(sec).
          maxT1 = max(T1);
          a1= length(original);
          t1 = 0:maxT1/a1:maxT1-(maxT1/a1);
          miny1 = min(original);
          maxy1 = max(original);
                    maxT2 = max(T2);
                    a2= length(voiced);
                    t2 = 0:maxT2/a2:maxT2-(maxT2/a2);
                    miny2 = min(voiced);
                    maxy2 = max(voiced);
          maxT3 = max(T3);
          a3= length(unvoiced);
          t3 = 0:maxT3/a3:maxT3-(maxT3/a3);
          miny3 = min(unvoiced);
```

```
        maxy3 = max(unvoiced);

  % To plot the original signal in number of samples and in time,
voice and unvoiced component.
        figure(1); subplot(411)
        plot(original); grid on

        axis([0 180652 -0.15 0.15]); xlabel('number of samples');
        title('Original speech waveform in number of samples');
                subplot(412)
                 plot(t1, original); grid on; axis([0 maxT1 miny1
maxy1])
                title('Original speech waveform in time');
        subplot(413)
        plot(t2, voiced); grid on; axis([0 maxT2 miny2 maxy2])
        title('Voiced component');
        ylabel('Amplitude (Unit)');
                subplot(414)
                plot(t3, unvoiced); grid on; axis([0 maxT3 miny3
maxy3])
                title('Unvoiced component');
                xlabel('Time, s');
```

Fig. 5.11 Command lines in M-file used to produce signals in Fig. 5.12

The M-file used includes the routine of converting the speech signal length from number of samples to time. This is done because in PSHF, the signal is processed base on the number of samples presented in it.

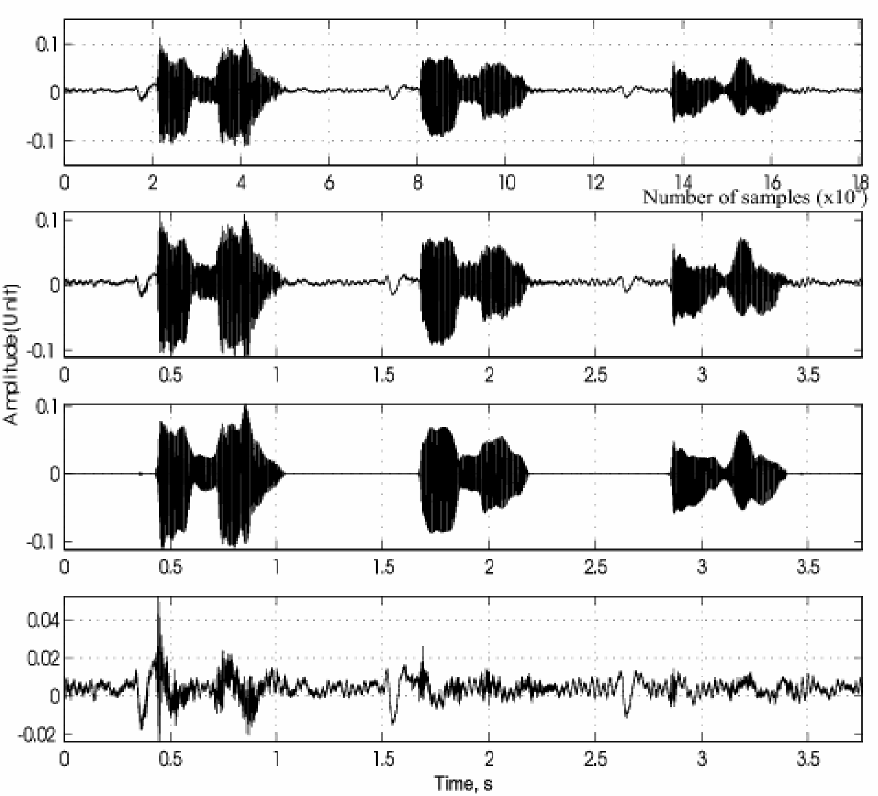

Fig. 5.12 Example of signal before and after PSHF. The original signal in number of samples (first), original signal in time before the PSHF (second), the voiced component (third) and unvoiced component (bottom) are signals after PSHF.

Note that the unvoiced component has relatively smaller amplitude than the voiced component.

Bad Examples

The command line follows is an example of bad initialization of –e option, and shows a two level of reporting (-T 2). The -e option should has a value calculated as signal length/number of estimated pitch periods, the final unit is in milliseconds. As a result of smaller value of -e than the appropriate one, the aperiodic component in third figure of Figure B.9 is missing between duration of 3.7-4.2 seconds and completely silent after about 5.5 seconds. Another thing that pointed out the error is the amplitude of the aperiodic component. Aperiodic component typically has very small amplitude compared to the periodic component.

```
../pshf -E 8 -e 3 -i 7 -d 2 -T 2 –S ./scriptfile.scp
```

```
 -- PSHF v3.10 by Philip J.B.  Jackson \& David M.  Moreno, (c)
2003 --

  nT = 39665, nSeg = 21289
  nT = 68761, nSeg = 28825
  nT = 83881, nSeg = 15317
  nT = 151841, nSeg = 44153
  nT = 177919, nSeg = 22739
  nT = 241707, nSeg = 42195
  nT = 265491, nSeg = 24447

in/CHS\_3\_sp\_azhaizhiuzhu.wav  out/CHS\_3\_azhaizhiuzhu
```

Fig. 5.13 shows A bad example when inappropriate external pitch sampling period (-e) was not calculated correctly. First - The original signal in number of samples, second - Original signal in time before the PSHF, third - the voiced component, fourth - unvoiced component after PSHF. Note that in the aperiodic component (third from top), part of the signal is missing between 3.7-4.2 seconds, and completely silent after about 5.5 seconds.

Also, the amplitude of the aperiodic component is not appropriate. Typically, it has very small amplitude compared to the periodic component.

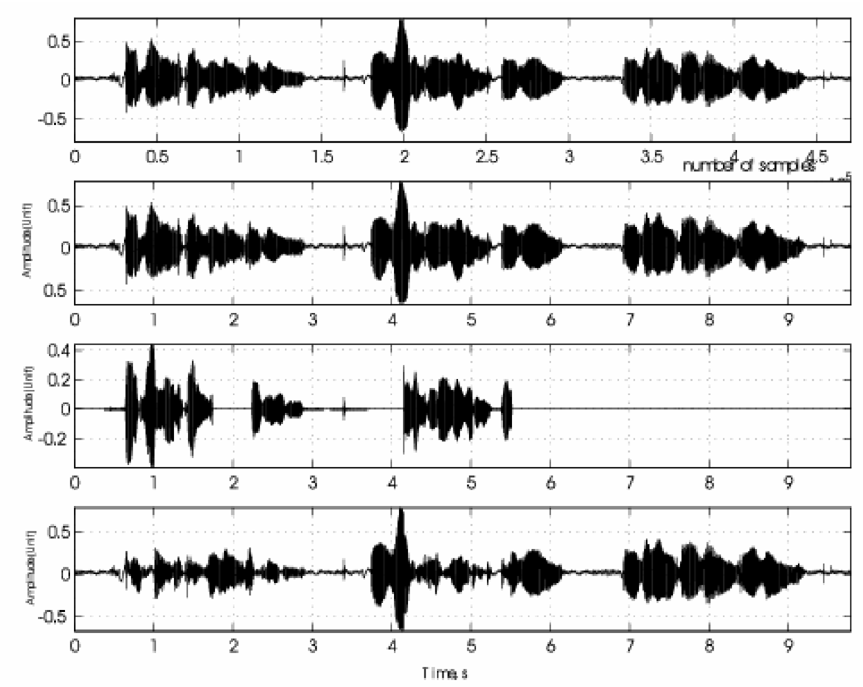

Fig. 5.13 A bad example when inappropriate external pitch sampling period (-e) was not calculated correctly.

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6

THE MODEL SYSTEM OF ELECTROPALATOGRAPH

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Chau Sheau Wei
Muhd Noorul Anam Mohd Norddin

INTRODUCTION

Speech station is used by the speech therapist in rehabilitation of a range of communication disorders. It is the combination of three types of speech therapy devices, which are Laryngograph (Electroglottograph), Nasal Airflow System and Electropalatograph (EPG). These three types of devices used different concepts to detect and analyzed the speech abnormalities of the patient. Laryngograph detect the vibrations of the vocal fold as well as simple movement of glottis, nasal air flow measures both nasal and oral airflow, EPG detects the contact between the tongue and palate, during speech. With the assistance of the speech station, the effectiveness of speech therapy is much more improved.

Electropalatograph is an electropalatography system. It detects and displays the dynamic motion of the tongue by using an artificial palate applied on the roof of the mouth. The artificial palate is custom made. The tongue contacts are displayed in tongue-palate contact patterns.

The Tongue

The tongue is a muscular organ in the mouth. It is the primary organ of taste and important in the formation of speech and in the chewing and swallowing of food.

The tongue, which is covered by a mucous membrane, extends from the hyoid bone at the back of the mouth upward and forward to the lips. Its upper surface, borders, and the forward part of the lower surface are free; elsewhere it is attached to adjacent parts of the mouth. The extrinsic muscles attach the tongue to external points, and the intrinsic muscles fibers, which run vertically, transversely, and longitudinally, allow it great range of movement. The upper surface is covered with small projections called papillae, which give it a rough texture. The color of the tongue, usually pinkish-red but discolored by various diseases, is an indication of health.

The tongue serves as an organ of taste, with taste buds scattered over its surface and concentrated towards the back of the tongue. In chewing, the tongue holds the food against the teeth; in swallowing, it moves the food back into the pharynx, and then into the esophagus when the pressure of the tongue closes the opening of the tranches, or windpipe.

It also acts, together with the lips, teeth, and hard palate, to form word sounds. It is the most versatile of the articulators, being involved in the production of all vowels and the vast majority of consonants. The versatility of the tongue allows:

i) Horizontal anterior/posterior movement of the body, blade and tip.
ii) Vertical superior/inferior movement of the body blade and tip.
iii) Transverse concave/convex movement.
iv) Spread/tapered contrast in the tongue blade and tip.
v) Degree of central grooving.

Different sounds required different tongue configurations. By altering tongue position and shape, the size of the oral cavity, and therefore its resonating characteristics, are changed. Fig. 6.1 shows human oral cavity and speech articulators.

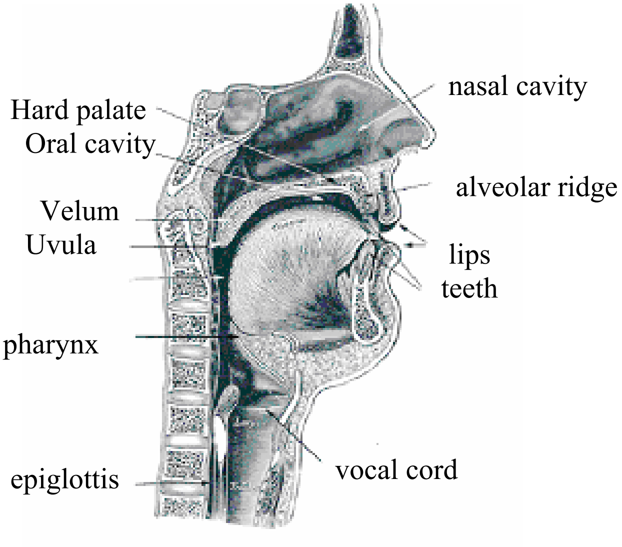


Fig. 6.1 Human vocal tract

The Palate

The palate is the roof of the mouth, separating the mouth from the nasal cavities. The palate consists of two portions: the hard palate in front and the soft palate behind. The hard palate is formed of *perioseum,* a bony plate covered by mucous membrane, and arches over to meet the gums in front and on either side. The soft palate is a movable fold of mucous membrane enclosing muscular fibers. Its sides blend with the *pharynx* (throat), but its lower border is free. It is suspended from the rear of the hard palate so as to form a wall or division between the mouth and the pharynx. During swallowing, this wall is raised to close the entrance to the nasal passages. A small cone-shaped structure, the uvula, hangs from the lower border of the soft palate.

The condition called cleft palate is a birth defect the results from incomplete development of the palate. It is characterized by a hole or gap in the palate that may extend from behind the teeth to the nasal cavity.

SPEECH PRODUCTION

The respiratory system is the source of power in nearly all speech sounds. The air stream from the passes between the vocal cords, which are two smalls muscular folds located in the larynx at the top of the wind wipe. If the vocal cords are apart, the air from the lung will have relatively free passage into the pharynx and the mouth. If the vocal cords are adjusted to have a narrow passage between them, the air stream will cause them to be sucked together. There will be no flow of air and the pressure underneath will be built to until hey are blown apart again. This caused them to be sucked together again and the vibrator cycle will continue. Sound produced when the vocal cords are vibrating are said to be voiced, and when they are apart are said to be voiceless.

The air passes above the vocal cords are known as the vocal tract. In the formation of consonants, the air stream through the vocal tract is obstructed in the same way. The arrow going from one the lower articulator to one of the upper articulator as shown in the figure below indicates some of the possible places of articulation. The required principal terms in the description of English articulations and the structures of the vocal tract involved, are; bilabial (the two lips), dental (tongue tip or blade and the upper front teeth), alveolar (tongue tip or blade and the teeth ridge), retroflex (tongue tip and the back part of the teeth ridge), palato-alveolar (tongue blade and the back part of the teeth ridge), palatal (front of tongue and hard palate) and velar (back of tongue and soft palate).

The articulators

a) The respiratory system
Speech sounds in the majority of cases, are powered by the expiratory phase respiration. During speech, a great deal of control is required.

b) The larynx
Air passes from the lungs to the larynx. For many of the speech sounds, the vocal folds are used to interrupt the flow of air, causing periodic pulses of air, or phonation. During speech, the frequency of vibration changes as pitch is changed in intonation

c) The pharynx
Its role in speech is that of a resonating cavity, the dimensions of which can be altered, e.g. shortened or lengthened, by raising or lowering the larynx

d) The velum
During normal respiration and the production of nasal consonant, the pharynx is coupled to the nasal cavity. However, for the vast majority of the consonant of English, the nasal cavity is closed while the velum is relaxed.

The additional places of articulation shown in the figure are required in the description of other languages. The 6 basic manners of articulation, which is used in these places of articulation are:

a) Stops
Stops involve of the articulators so that the air stream cannot go out of the mouth. There is said to be nasal stops if the soft palate is raised so that the nasal tract is blocked off, the air stream will be completely obstructed. The pressure in the mouth will be built up an oral stop will be formed.

b) Fricatives
A fricative sound involves the close approximation of 2 articulators. This cause the air stream is partially obstructed and a turbulent airflow is produced.

c) Approximants
When one articulator approaches another but does not make the vocal tract so narrow that the turbulent air stream results, the approximants are produced.

d) Trills
A trill results when an articulator is held loosely fairly close to another articulator, so that it is set into vibration by the air stream.

e) Taps
If one articulator is thrown against another, as when the loosely held tongue tip makes a single tap against the upper teeth or the alveolar ridge. A tap is produced if one articulator is thrown against another.

f) Laterals
When the air stream is obstructed in the midline of the oral tract, and there is incomplete closure between one or both sides of the tongue and the roof of the mouth, the resulting sound is classified as a lateral.

THE ELECTROPALATOGRAPH (EPG)

EPG is a device that uses an artificial palate applied to the hard palate to detect and display the dynamic motions of the tongue. Electroplatography is an instrumental technique for determining tongue/palate contact pattern during speech. EPG is an extremely useful additional tool, when used in conjunction with conventional therapy techniques. Electropalatography allows objective assessment, enabling appropriate targeting of therapy. It provides visual feedback, which assists in therapy and can be extremely motivating for therapist and patient. Besides, it gives an objective measurement of outcome, which is an increasingly important consideration for the therapist.

The main applications of EPG are:

1. Training a person in articulation handicaps

    - Due to auditory and other sensory deficit.
    - Due to motor co-ordination problems
    - Due to functional articulation difficulties.
    - Structural abnormalities, e.g.: cleft palate

2. Basic phonetic research into lingual articulatory motions and configurations.

Both the therapist and patient can use the EPG. The general strategy in using the technique for diagnosis is to compare the patterns of tongue contact for a pathological speaker with those of a normal speaker and to interpret the differences in terms of lingual gestures.

The Artificial Palate

The artificial palate studded with 62 small electrodes, each one 1-2 mm. The electrodes are arranged in 8 rows. Each row has 8 electrodes apart from the first row, which has only 6 electrodes because the mouth is narrower toward the front teeth. The electrodes are divided into 3 zones (alveolar-palatal-velar) as shown in Fig. 6.2.

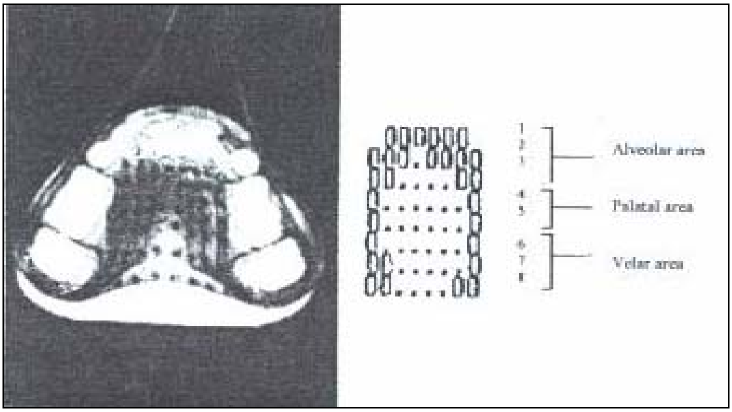


Fig. 6.2 The artificial palate and the 3 zones

The palate is custom-made and simply clips to the upper teeth. A plaster cast of the upper palate and the teeth is the initial requirement from the end user. The palate are supplied complete with insulated wires from each electrode and connected to a signal conditioning circuit, which collects contact data from the palate and pass it to a computer. Fig. 6.3 shows different types of acrylic palates.

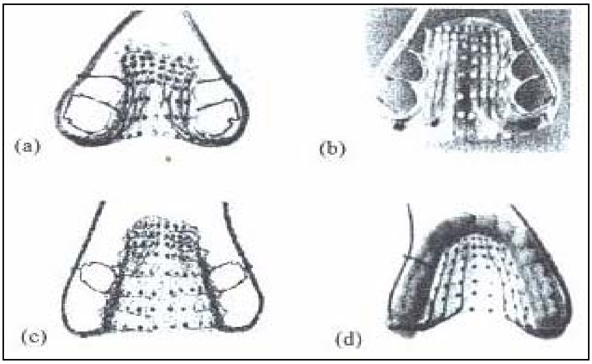


Fig. 6.3 Four different acrylic palates: a) is for a cleft palate child, b) and c) are normal palates and d) is duplicate denture for a 60-year old apraxic speaker.

Tongue Dynamic

EPG contact patterns reveal stop/fricative/lateral approximant articulations in the alveolar regions very clearly, as well as palatal and velar articulations. General advanced/retracted tongue settings can also be observed in the contacts at the side of the mouth during vocalic articulations.

When the tongue touches an electrode, it completes an electrical circuit and a very low current flow. The grid of electrodes records the position of the tongue 100 times per second. This information is passed to a computer, which displays it on a series of grids that match the arrangement of the electrodes and shows how consonantal stop and fricative articulations develop in time. The tongue dynamics is represented by the tongue-palate contact patterns in real time. Fig. 6.4 shows contact patterns for word 'TACTICS'. Besides, the contact patterns can be also shown by the number of the contact touched in a particular area of the palate as a function of time (Fig. 6.6).

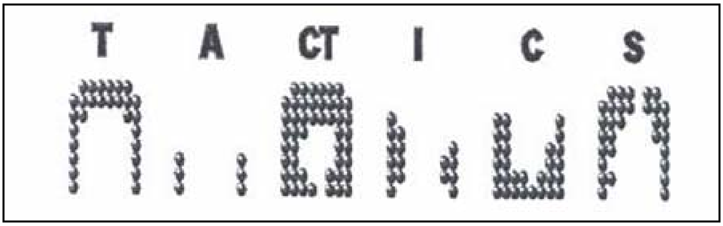


Fig. 6.4 Tongue-palate contact patterns

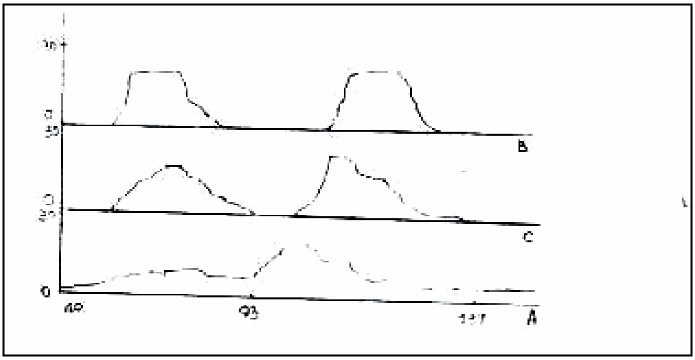
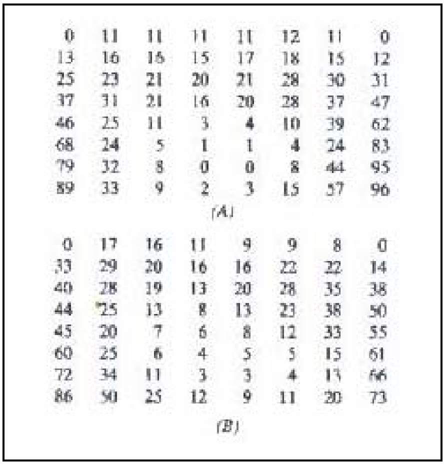


Fig. 6.5 The total contact that occurs in the alveolar area (A), the palatal area (B) and the velar area (C) for the word ‘tractor’

The tongue contact also can be represented by the number of times a given palatal electrode was touched during production of speech as shown in Fig. 6.6.



0	11	11	11	11	12	11	0
13	16	16	15	17	18	15	12
25	23	21	20	21	28	30	31
37	31	21	16	20	28	37	47
46	25	11	3	4	10	39	62
68	24	5	1	1	4	24	83
79	32	8	0	0	8	44	95
89	33	9	2	3	15	57	96

(A)

0	17	16	11	9	9	8	0
33	29	20	16	16	22	22	14
40	28	19	13	20	28	35	38
44	25	13	8	13	23	38	50
45	20	7	6	8	12	33	55
60	25	6	4	5	5	15	61
72	34	11	3	3	4	13	66
86	50	25	12	9	11	20	73

(B)

Fig. 6.6 Contact frequency for two speaker A and B

Touch Sensing

The touch sensing input devices shown in Fig. 6.7, which senses contact from the user's hand, no pressure or mechanical actuation of a switch is necessary to trigger the touch sensor. The "touch sensors" are conductive surfaces on the exterior of the device shell that are applied using conductive paint. The conductive paint is then connected internally to the touch sensing circuitry. The internal circuitry generates a 30 Hz square wave that is present on the conductive paint pad.

The parasitic capacitance of the user's hand induces a slight time delay in this square wave. When this time delay passes a critical threshold, a *Touch* or *Release* event is generated. A potentiometer allows adjustment of this threshold to accommodate conductive surfaces of various sizes; this only needs to be set once when the circuit is constructed. To provide a good coupling with the tactile feedback that the user feels, the capacitance sensors are set to generate *Touch/Release* events only and exactly when the user's hand actually makes (or breaks) contact with the surface.

When providing multiple touch sensors with the circuit described above, the 30Hz square waves can pass through the user's body and be picked up by another touch sensor as a false *Touch* or *Release* signal. Thus, to avoid interference, all devices that the user may be touching at a given time should be synchronized to the same square wave.

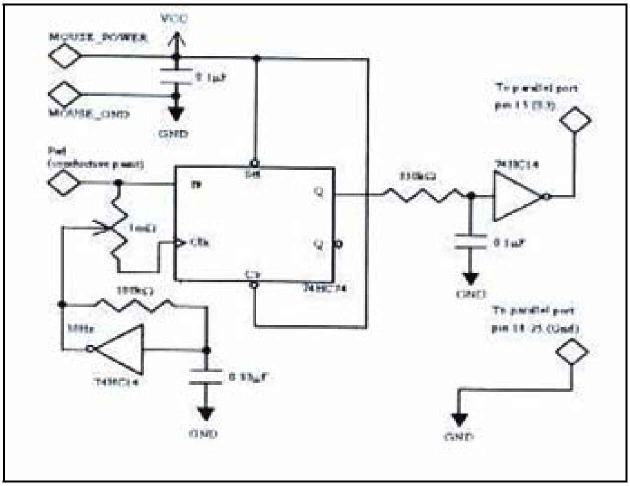


Fig. 6.7 Circuit diagram for a single touch sensor

The properties of touch-sensing devices are:

i) No moving parts for the touch sensors.

ii) Touch sensors require no mechanical intermediary to activate them.

iii) Operation by feel

Touch sensors can be arranged into regions that act like a physical template on a touch tablet. The user can feel the touch-sensing regions without looking at the device or at the screen. This can reduce the time that would be required to switch between devices or widgets on the screen.

iv) Feedback

Touch sensors differ from traditional pushbuttons in the amount and type of feedback provided. For cases where a touch sensor is being used in an implicit role and is not being used to simulate such devices, however, such feedback may not be needed or even desired.

v) Accidental activation
Because touch sensors require zero activation force, they may be prone to accidental activation due to inadvertent contact. In particular, when touch sensors are used to trigger explicit actions, care needs to be taken so that the user can rest his or her hand comfortably on the device without triggering an undesired action.

vi) Flexible form factor
Unlike a touch pad, which generally requires a planar form factor, touch sensors can have an extremely flexible shape; curved surfaces, uneven surfaces, or even moving parts such as wheels and trackballs can be touched sensitive. Touch sensors also have a near zero vertical profile, which allows them to be used in tight spaces that may not readily a traditional pushbutton.

vii) Unobtrusive
Touch sensors can be added to a device without necessarily making it look complex and cluttered with buttons. The user may not even have to be aware that the device incorporates a touch sensor.

viii) Low overhead to disengage
The proximity signals provided by a tablet and the touch signals and a touch sensor support logically distinct device states.

ix) Deactivation from software
Touch sensors lend themselves to deactivation from software, because a touch sensor does not respond to user input with a physical “click”. Thus, unlike a pushbutton, a disabled touch sensor does not offer any false physical feedback when it is touched, which is useful if the user is in a context where the action is

not valid or if the user does not want an added feature.

x) Additional physical gestures

Some gestures that are not captured well by pushbuttons can be captured by touch sensors. A pushbutton that includes a touch sensor can capture these gestures.

Touch Operated Switch

Operation methods of the touched operated switch:

a) Hum

Mains wiring causes an electrical hum field. This is picked up on the body and can be easily detected by almost any high impedance input device.

b) Leakage

Apply a DC voltage between earth and any touch paint and a person touching it will allow the voltage to a leakage current away to earth. Not as reliable as mains hum since skin resistance varies wildly from person and also depends on the person's age and emotional state, as well as on the atmospheric humidity.

c) Capacitance

This requires an oscillator as well as the detector but can be more reliable because it doesn't rely on hum or leakage or any other variable effect.

d) Heat

Most semiconductors are heat sensitive and can detect skin temperature. Main problem is the time delay as heat flows from a finger to the semiconductor, so more of an interesting idea than a practical solution.

e) Light reflection
A finger will reflect light.

f) Light transmission
A finger will reduce light falling on a detector but this will usually rely on ambient lighting so it is not suitable for a lot of uses.

g) Acoustic damping
It has an oscillator, which drive a piezo (crystal) earpiece. Once started, a finger touch the earpiece will stop the oscillator. A loud noise will start it again.

h) Motion
The movement of a finger close to the detector could operate a switch.

METHODOLOGY

This section will focus on the explanation on the design of each block in the block diagram and the implementation of the software to read data and display it in tongue palate contact patterns.

In the EPG system, the artificial palate is important to detect the contacts between the tongue and the palate. The detected contact signals are sent to a signal conditioning circuit and an electronic unit to be processes and displayed in tongue-palate contact patterns in real time. However, in this project, due to some financial problems the artificial palate was not used. It was replaced by 62 touch sensors, which were made of metal or conductor. Therefore, the sensors will sense human contact, which represent the tongue contact because the sensors too large to put in the mouth. Besides, the software would not display the tongue-palate contact patterns in real time too, since there was no interface between the hardware and the software.

The main task of the project are to design a circuit to detect human contact and display it on LED display and software to read data from file, which represents the tongue contact data, and display the data in tongue-palate contact patterns. The software was designed so that it is able to capture data from the hardware if there is in interface between them.

The circuit is simple. It consists of 62 latches, which are arranged in parallel configuration, a 6V voltage regulator, 62 touch sensors (palate) and an LED display, which are in the same arrangement of the electrodes on the artificial palate. D latches are used to pick up the human contact. Each of the *D latches* controls a touch sensor and an LED that represents the equivalent position of the sensor on the LED display. The display is arranged so that, when the user touches the left-hand-side of the palate, LED's on the right-hand-side of the display light up (refer Fig. 6.8).

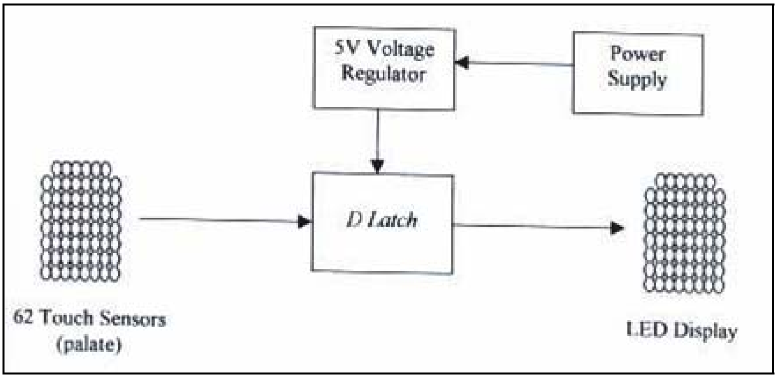


Fig. 6.8 Block diagram of EPG model system

RESULTS

The hardware is required to light up the LEDs on the Led display when the touch sensors on the palate are touched at the equivalent position. For example, when a user is touching a row of the sensors at the bottom of the palate, a row of LEDs at the bottom of the LED display are on the same time as shown in Fig. 6.9. If the user removes his/her hand, the LEDs would change to 'off' state. When the user continues to touch the other sensors on the palate, the LEDs at the equivalent position on the LED display light up continuously to show the movement of the user's hand.

The system would not delay the period of 'on' state of the LED. It should show the dynamic motions of the tongue movement (it is actually the hand movement) because the movement of the tongue is continuous. The time delay of the 'on' state of LED would not show the actual movement of the tongue.

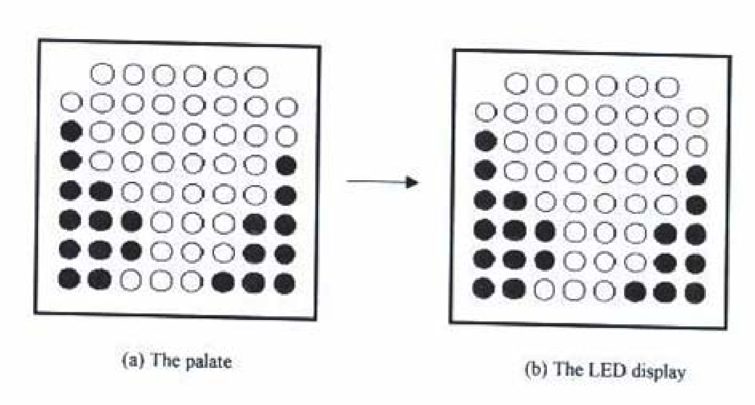


Fig. 6.9 The palate when it is touching and the condition of the LED display

The results of software are displayed in two modes on the screen. Mode 1 will display the tongue-palate contact patterns one by one on the screen as the user pronounces some alphabets or some words (however, at the movement, the tongue-palate contact patterns are displayed by reading the contact data from data file). In Mode 2, all the contact patterns that were displayed in Mode 1 are displayed on a group of palates in a group for displaying the different contact patterns. By using Mode 2, the users can see each contact patterns clearly.

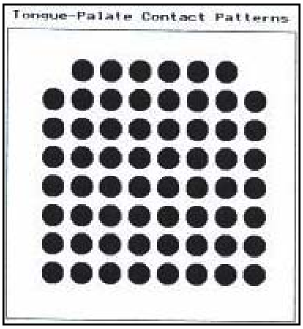


Fig. 6.10 Enter the correct file name during blank palate

As indicated in Fig. 6.10, the program asks the user to enter the name of the file, which is going to be opened. When the user enters a wrong file name, the program tells the user that the file cannot be opened then asks the user to try again. However, the user is only given a chance to try. If the user still enters a wrong or invalid filename, the program will tell the user again and then exit from the system.

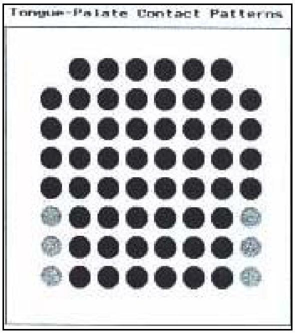


Fig. 6.11 The contact patterns when pronouncing ‘a’

Some data files that contain the contact data for the tongue-palate contact patterns when pronouncing alphabet/word were created. The program will read these data and then display them on the screen as tongue-palate contact patterns. Fig. 6.11 shows the tongue-palate contact when pronouncing an alphabet ‘a’.

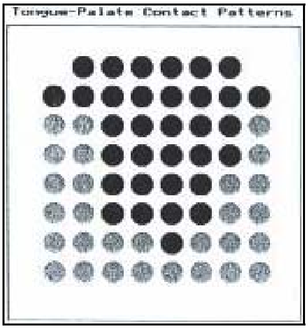


Fig. 6.12 The contact patterns when pronouncing ‘c’

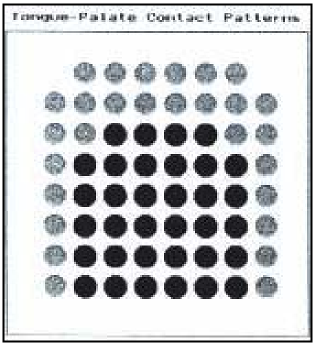


Fig. 6.13 The contact pattern when pronouncing ‘t’

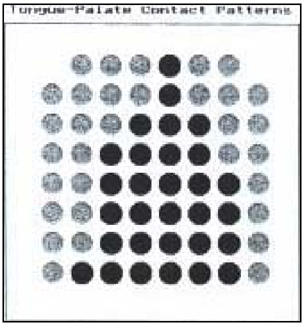


Fig. 6.14 The contact pattern when pronouncing ‘s’

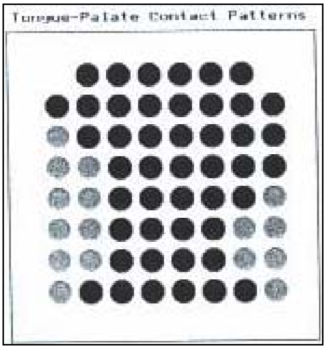
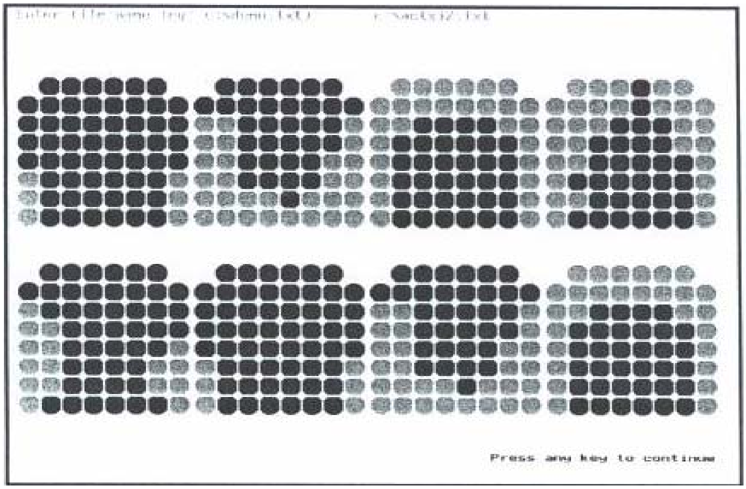


Fig. 6.15 The contact pattern when pronouncing ‘i’

Fig. 6.11-6.15 show the tongue-palate contact patterns when a user pronounce the alphabet ‘a’, ‘c’, ‘t’, ‘s’ and ‘i’, respectively. When the user pronounces these alphabets continuously, the program will also display each contact pattern continuously. This illustrates the dynamic motions of the tongue movement.

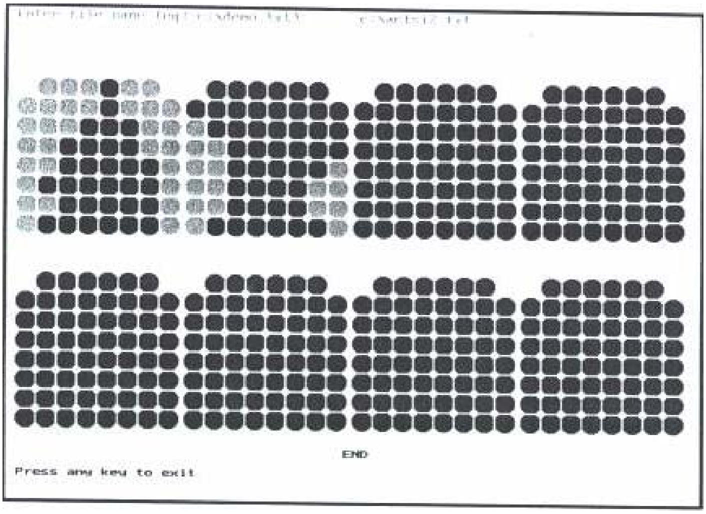
As shown in the figures, there are three different keys for the user to choose. The user presses <ESC> key to exit the system, <SPACEBAR> key to repeat displaying the contact patterns, <TAB> key to enter Mode 2.



```
Enter file name (eg: c:\sdum.txt)        c:\actg12.txt

                                              Press any key to continue
```

Fig. 6.16 The tongue-palate contact patterns in Mode 2 (part I)



Enter file name [illegible]

END

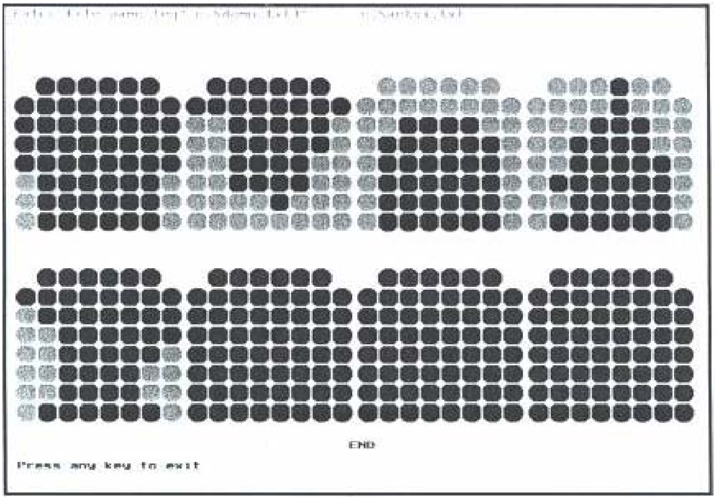
Press any key to exit

Fig. 6.17 The tongue-palate contact patterns in Mode 2 (part II)

In Mode 2, all the tongue-palate contact patterns are displayed on different palates, as indicated in Fig. 6.16 and Fig. 6.17. Both figures showed the contact patterns for pronouncing the alphabet ‘a’, ‘c’, ‘t’, ‘s’ and ‘i’, for two times. Thus, there are ten contact patterns to be displayed. Due to there are only eight patterns can be displayed at a time, the last two contact patterns are displayed on the next screen.

The program will wait for the instruction of the user to continue displaying the following patterns on the next screen after the first group of the contact patterns (eight contact patterns in a group). When there are no more patterns to be displayed, the program will tell the user by displaying a word ‘END’ on the screen and ask the user to press any key to exit the system.

However, when there are only eight contact patterns or less, the program will display all the contact patterns at the first time. For example, when a user pronounce four alphabets ‘a’, ‘c’, ‘t’, ‘s’ and ‘i’ continuously, there are only four patterns is less than eight patterns. The program will display all these patterns on four of the eight palates on the screen (Fig. 6.18).



```
[illegible]

                              END
Press any key to exit
```

Fig. 6.18 The tongue-palate contact patterns in Mode 2 (part III)

CONCLUSION

The EPG model system is divided into two parts, which are hardware and software. The hardware part detects the human contacts and displays it n an LED display. The software part reads the contact data from data file and displays it in tongue-palate contact patterns. This software is actually designed for the use of real time displaying. If there is an interface between the software and hardware and the artificial palate is used, the tongue palate contact patterns can be displayed in real time modifying some parts of the program.

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7

THE ELECTROPALATOGRAPH SOFTWARE

Rubita Sudirman
Chiang Yok Peng

INTRODUCTION

The Electropalatograph Software is a Windows® based software which is developed using Microsoft® Visual C++ 6.0. This software will receive data from an electropalatograph device via a parallel port. This software will then detect the tongue — palate contact pattern. This pattern will be manipulated and displayed on the screen. Subsequently, this pattern can be compared with existing patterns in the library. The Electropalatograph Software provides a few methods of comparison. With these resources a patient having difficulty in speech can be taught to improve their speech. This software also provides a built in help file which be a great assistance to new user and those who are not familiar with electropalatograph software.

A simulation software is used as a virtual device to test this software. This simulation software has an artificial palate which consists of 62 sensors on the artificial palate itself This simulation software would make it easier for user to understand the Electropalatograph software.

The driver software will read from the parallel port and write to a file.The driver receives data in hexadecimal but writes it in binary format. The driver will read the data every time the data available signal is high, in this case it is the busy signal. The driver will stop reading when there is a pause of around 10 seconds or if 12 patterns have been read.

The Electropalatograph software also has reference and diagnostic function in its main module. These functions are to further analyze the tongue — palate patterns of the patient.

THE TOUNGE

The tongue is an important muscular organ in the mouth. Its serves three major functions which are the formation speech , the organ of taste and the chewing and swallowing of food.

The tongue extends from the hyoid bone at the rear of the mouth until the lips. The tongue is covered by a mucous membrane. Most parts of tongue are not in contact with any other parts in the mouth, these would include the upper surface, its borders and the forward part of the lower surface.

This would give the tongue a great freedom of movement. The upper surface of the tongue is covered with papillae. The color of the tongue can be a good indication of the health of a person. The normal color of the tongue is pinkish — red.

There are taste buds scattered over the surface of the tongue, thus making the tongue an organ of taste. The tongue also assists the chewing process by holding the food between the teeth. The tongues also moves the food back into the pharynx and then into the esophagus. This process is commonly known as swallowing.

The tongue with the lips, teeth and the hard palate plays a major role in speech formation. Being the most agile and versatile of all the organs listed above, the tongue is involved in most of the production of consonants and vowels. The tongue is free to move in much direction. These would include transverse concave movement, central grooving, horizontal/vertical anterior/posterior movement of the body blade and tip, spread/tapered contrast in the tongue blade and tip.

Various sounds would certainly require different tongue position and configuration. The resonating characteristic would change when the tongue position and shape and when the size of the oral cavity is changed.

THE PALATE

The palate is the upper part of the mouth. It is also known as the roof of the mouth. The palate separates the mouth from the nasal cavities. The palate is divided into two parts which are the hard palate and the soft palate. The hard palate is in the front and the latter is located at the rear. The soft palate is movable mucous membrane which has muscular fibers in it. Where as the hard palate is formed by a bony plate which is covered by mucous membrane. The soft palate is suspended on the rear of the hard palate. The soft palate forms a kind of wall between the pharynx and the mouth. In the swallowing process this wall is raised up to allow food to enter. The defect called cleft palate is the condition of incomplete development of the palate. A person who has this defect would have a hole or gap in the palate which could occur anywhere along the hard and soft palate.

SPEECH PRODUCTION

The source of almost all speech sounds is produced by the respiratory system. This occurs when the air stream passes the vocal cords. Generally the vocal cords are two muscles located in the larynx. When the vocal cords are apart air can flow freely
from the lungs to the mouth. But when the vocal cords are together there would be a narrow passage for the air stream to flow. What happens here is the pressure is built up until the vocal cords are blown apart. Then the vocal cords are sucked together again and this cause a vibration cycle. It is this vibration pattern which produces sound. In short sound is produced when the vocal cords are together.

Vocal tract is the air that travels above the vocal cords. Basically, the same process occurs to the vocal tract in the formation of constant In a normal human being there are four articulates that make up the human speech and sound:

a) The respiratory is the power source of sound.
b) The pharynx plays the function of a resonating cavity.
c) The larynx. It is where the vocal cords are located. It is responsible of the control of frequency and intonation. As explained earlier it causes periodic pulses of air. This periodic pulse is also known as phonation.
d) The velum is not used much in the production of the English language. It is used in other language.

MANNERS OF ARTICULATION

a) Trills - It occurs when two articulates are quite close to each other. It will vibrate when an air stream passes by.
b) Taps - This occurs when one articulator is thrown against another. For example when the tongue is thrown against the palate
c) Stops - A stops involves the closure of the articulates so that the air stream cannot go out of the mouth. This means air can only come out through the nose. An oral stop occurs when air cannot come out from the mouth completely
d) Fricatives - Fricatives is produced when the air stream is partially obstructed and a turbulent airflow is produced.
e) Approximants - This occurs when one articulate is approaching another but no vocal tract is made. The turbulent air stream causes the approximants to be produced.
f) Laterals - Laterals are produced when the air stream is obstructed in the midline of the oral tract. There is incomplete closure between the tongue and the palate.

ELECTROPALATOGRAPH (EPG)

EPG is a device used to detect the dynamic movement of the tongue by capturing its contact pattern a^{g}ainst the palate. Thus this method requires an artificial palate. EPG is basically used as an additional tool of speech therapy. EPG is used to determine the exact problem or problems and to determine the therapy that needs to be used. The visual feedback is also useful to provide patients and therapist a gauge of improvement and advancement. The area few condition in which EPG would be necessary and useful. There are:

a) motor coordination problems
b) dysfunctional articulation
c) structural abnormalities
d) sensory deficit
e) auditory deficit

THE ARTIFICIAL PLATE

The artificial palate is studded with 62 electrodes. These electrodes are arranged in 8 rows with the upper most row having 6 electrodes (Fig. 7.1). The artificial palate is clipped to the teeth. The wires used are completely insulated to ensure the safety of the patients. The data collected from the electrodes are then passed on to a computer for further processing.

EPG contact patterns would show articulations very clearly. It could reveal stops, fricatives and lateral approximations. Generally it would reveal things that cannot be known by normal speech therapy. When the tongue touched the electrodes the electrodes generate a signal. This signal is then sent to the computer through the two insulated wires. Each electrode will send separate signal through the wires. Fig. 7.2 shows examples of EPG patterns.

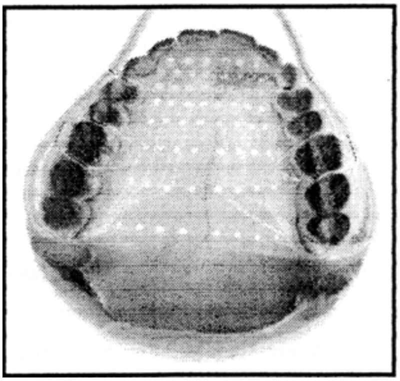


Fig. 7.1 The Artificial Palate

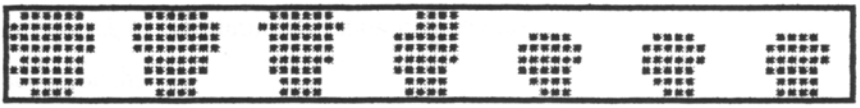


Fig. 7.2 Examples of tongue – palate contact pattern

BLOCK DIAGRAM OF THE EPG SOFTWARE

This software has three major parts that contribute to the major design. There is also a help program created for the benefit of the users- They are:

1) The main module
2) The driver
3) The simulator

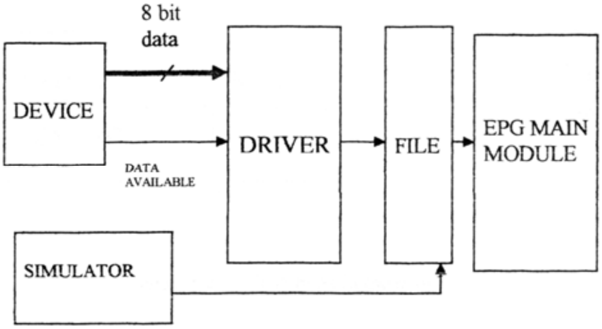


Fig. 7.3 Block Diagram of the EPG Software

Fig. 7.3 illustrates how data is entered through the driver into a file. In the same way the simulator can be used to enter data into the file. Data is then retrieved by the main module and further processing is done. Simply said the driver and simulator are the hands of the EPG main module. As can be seen the final data or graphical data is available only in the EPG main module. Any error at the device or data stage would cause wrong data to enter to the main module.

THE MAIN MODULE

The main module is the brain of the EPG software. It is built in a Single Document Interface (SDI) style. All the processing and graphical display is found the main module. The main module links all other parts of this software. The main module also can be divided into three parts and these parts are interconnected and must be done in sequence.

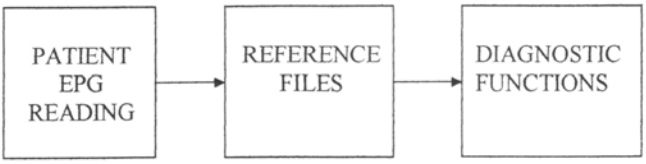


Fig. 7.4 The parts in the main module

PATIENT EPG READING

The first block of Fig. 7.4 is where the input of the patients EPG reading is collected and displaed.

There are four main functions in this part :

a) Connect to device
This function calls the driver out. This is to connect the Electropalatograph device. This function is done by using the 'WinExec' Function'. The `WinExec'function is an in built Visual C++ function which calls out another windows program.

b) Simulate
This function calls out the EPG Simulator. It also use the `WinExec' function

c) Display
This function reads data that is written by either the driver or the simulator. It then displays the data in the MSFlexgrid object. The MSFlexgrid object is an ActiveX object created by Microsoft®. MSFlexgrid is actually an excel spread sheet. This function actually updates the output screen which is the MSFlexgrid object. Here the command 'SelTextArray (ID)' is used to plot the data on the screen as squares or simply said touch patterns. It reads the data one by one and plots it according the ID provided. The ID is generated by a mathematical equation.

J + 1, I + (K × 11)

Where

J = row
I = Column
K = Pattern number

d) Save file

It is to save the pattern of the patient into the hard disk or anywhere else desired. Firstly this function uses the 'Do Modal' function. The 'Do Modal' function is an inbuilt function in Visual C++. This function would call out a save/open dialog box. This dialog box is similar to the dialog box that comes out when we try to save a Microsoft Word document. This function is altered to fit the use of this program. The first alteration done is that the function is turn to save mode. Then it is changed so that it only allows saving files in EPG format. Next the function is manipulated to display only EPG files. The next this function does is writes data that is in the screen into the file that is selected or created.. The data is extracted from the buffer and then written in binary format in the file. Here the 'CFiIe' command is used .Before writing the file we have to specific a few parameters. These parameters are the length of the file, the file name and the starting point. These parameters are supplied in this program as a default value.

REFERENCE FILE

This part has only two functions:

a) Open File
This function opens files to be displayed in the reference output. The reference output is also an MSFlexgrid object. The function calls out the 'Do Modal' function and then the user select the file to be opened. The 'Do Modal' function is altered to open files this time. The file type is set to EPF files. Then the CFile command is used to read data from the reference file. To be noted the reference file is in binary format. Then the data which is read is then transferred to the MSFlexgrid object using the “SetTextArray (ID)” function.

b) Save File
This function does the same thing the save file in the previous section.

DIAGNOSTIC FUNCTION

There are three diagnostic functions

a) Find Match
Find match is a procedure that finds the matching patterns between the reference file and the patients contact pattern. Then the data is displayed on the reference output which is an MSFlexgrid object. The method of comparing is by using the if - else statement. If both the data form the patient and the reference are the same then a square is plotted on the dia^{g}nostic pane. The process is repeated until all data is processed- When no speech pattern is produced the find match will not compared it with a speech. It will not process the no speech sections.

b) Find Mistakes

This function locates the mistakes done by the patient. It finds the places where the patient is supposed to have the tongue palate touch pattern. This procedure is done the same as the find match except this procedure looks for patterns that are in the reference but not in the patient pattern. This function could diagnose the exact difficulty of a patient. For example a certain patient has difficulty placing the tongue in certain positions.

c) Find Correction

Find Correction is the opposite of find mistakes. This procedure looks out for patterns that are in the patients speech but not found in the reference file. The algorithm of this procedure is opposite of that of 'Find Mistakes'. This algorithm looks out for patterns that are in the patients tongue – palate touch patterns but not in the reference patterns. Find correction function is to find unwanted tongue - palate patterns.

THE EPG SIMULATOR

The simulator is a program that tries to imitate the function of the driver. The simulator is useful for testing purposes and helping people understand EPG. In the simulator software there are 124 check box buttons representing the electrodes in the artificial palate. Each of these boxes is given a value and if it is pressed it would give a high signal. After pressing the desired buttons the write and simulate button updates the pattern to the file. This program is also done in the dialog box style.

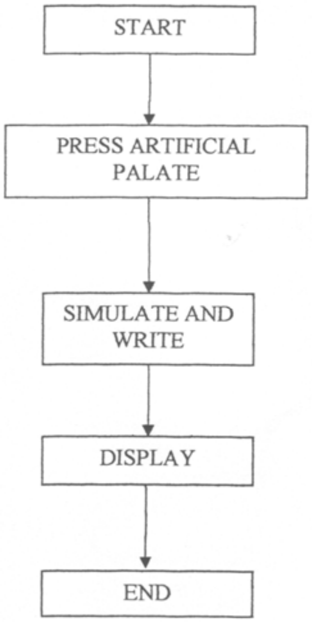


Fig. 7.5 Flowchart of the EPG Simulator

THE HELP PROGRAM

A help program is created to aid a person to understand EPG, the software and its capabilities. It is created in a dialog box style. It is created with a dropdown menu to choose the help topic. Once the display button is pressed the help topic is displayed on the screen. Each of the topics is assign a variable, and when it is chosen this variable activates the data. This data is then printed to the screen using an MSFlexgrid Object.

RESULT

The end product of this project is a single document type interface with multiple functions. The main module of the EPG software interface is as Fig. 7.1 and the EPG Simulator is as Fig. 7.7.

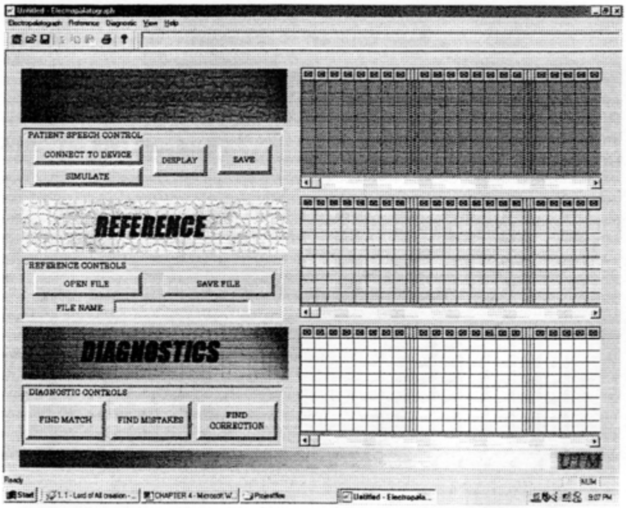


Fig. 7.6 The EPG main module window

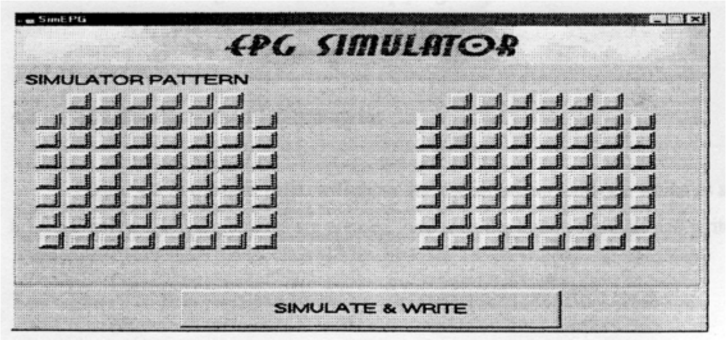


Fig. 7.7 The EPG Simulator Interface

The Result of the EPG Simulator

Fig. 7.8 and 7.9 showed that the simulator software works as an artificial palate. First the buttons are pressed, then the button "simulate & write" is pressed.

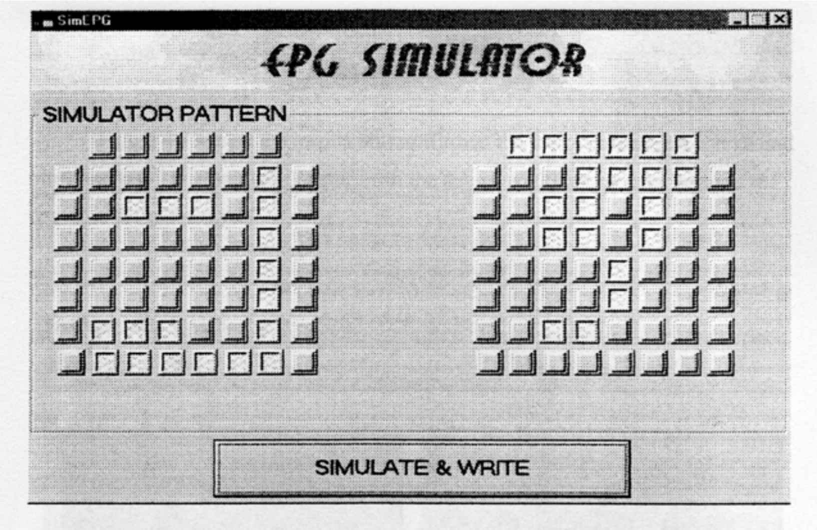


Fig. 7.8 The simulator buttons are pressed

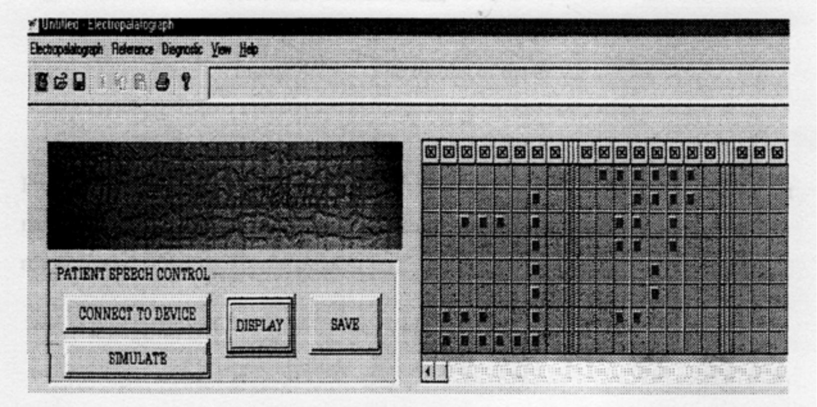

Untitled - Electropalatograph
Electropalatograph Reference Diagnostic View Help
PATIENT SPEECH CONTROL
CONNECT TO DEVICE
DISPLAY
SAVE
SIMULATE

Fig. 7.9 The results after the display button is pressed

The Results of the Driver

Fig. 7.10 shows the results obtain^{e}d when the data available pin is high and pin l and pin 2 is grounded. Testing with the device could not be done because the device is fully functional.

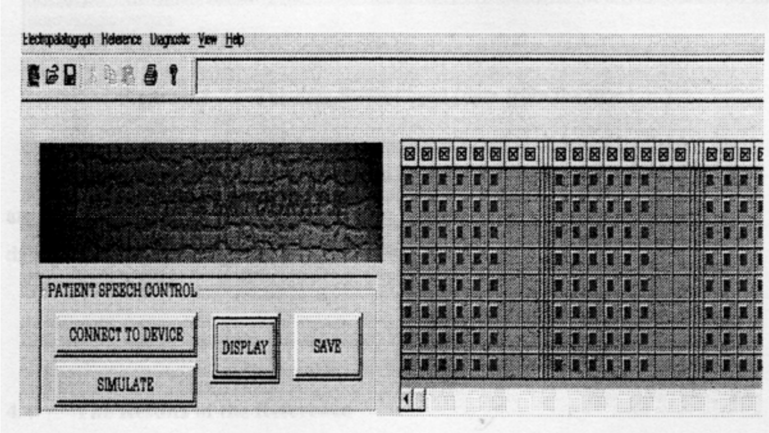
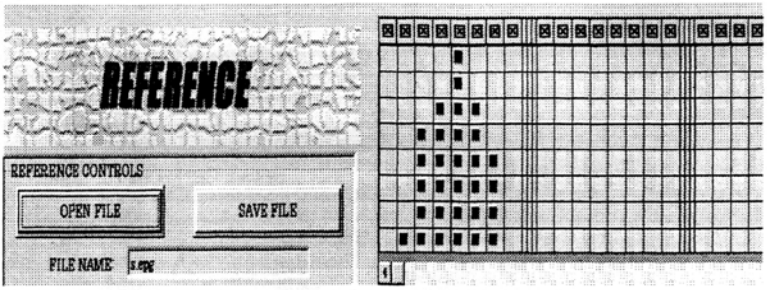


Fig. 7.10 The results of the driver

From the diagram above we can see that the 7th and 8th columns from the left are not marked. This shows that the pin 1 and pin 2 retrieves data to column 8 and column 7 respectively.

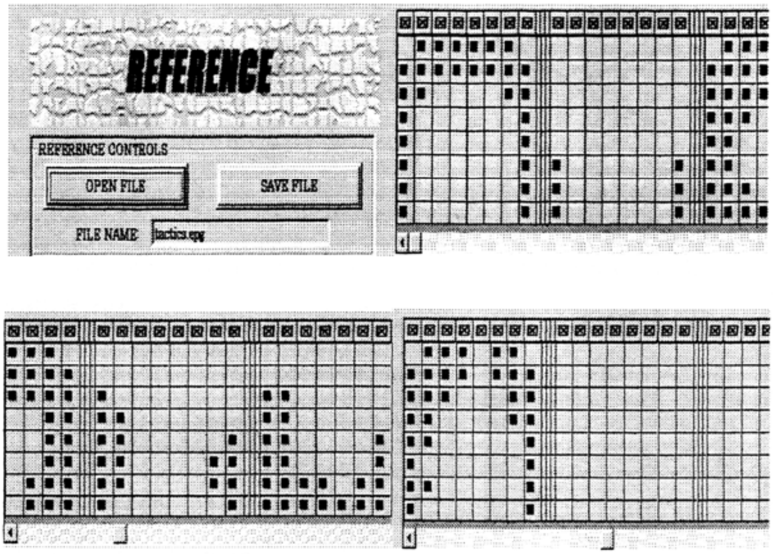
The Results of the Reference

The library file is opened using the open file function. For example, the letter s (Fig. 7.11) and the next is the word "tactics". In Fig. 7.12 the word "tactics is" displayed in the reference pane. The slider can be moved to view the latter patterns.



FILE NAME s.epg

Fig. 7.11 The letter S in the reference pane

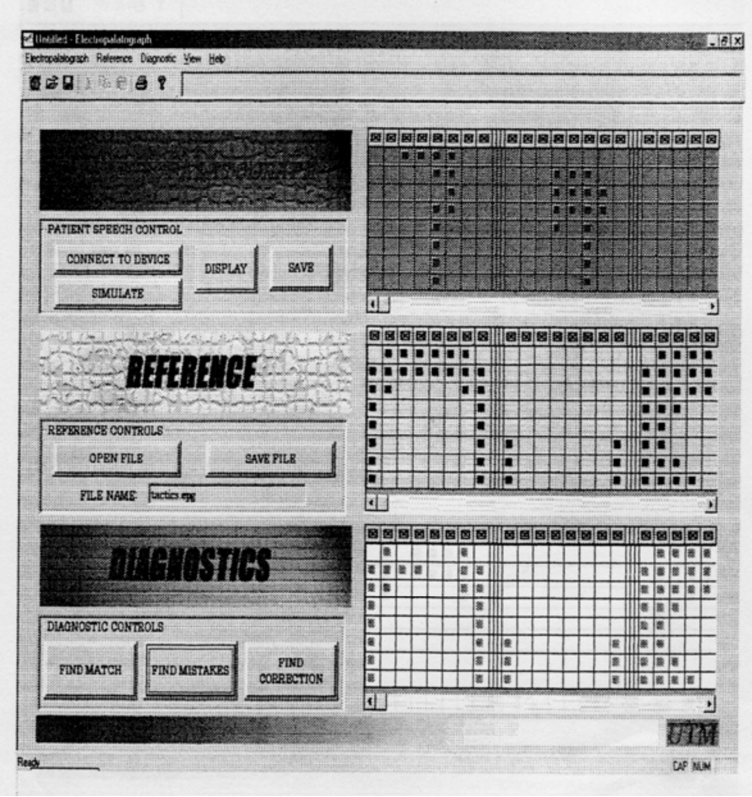


FILE NAME tactics.epg

Fig. 7.12 The word tactics in the reference pane

The Results of the Diagnostic Functions

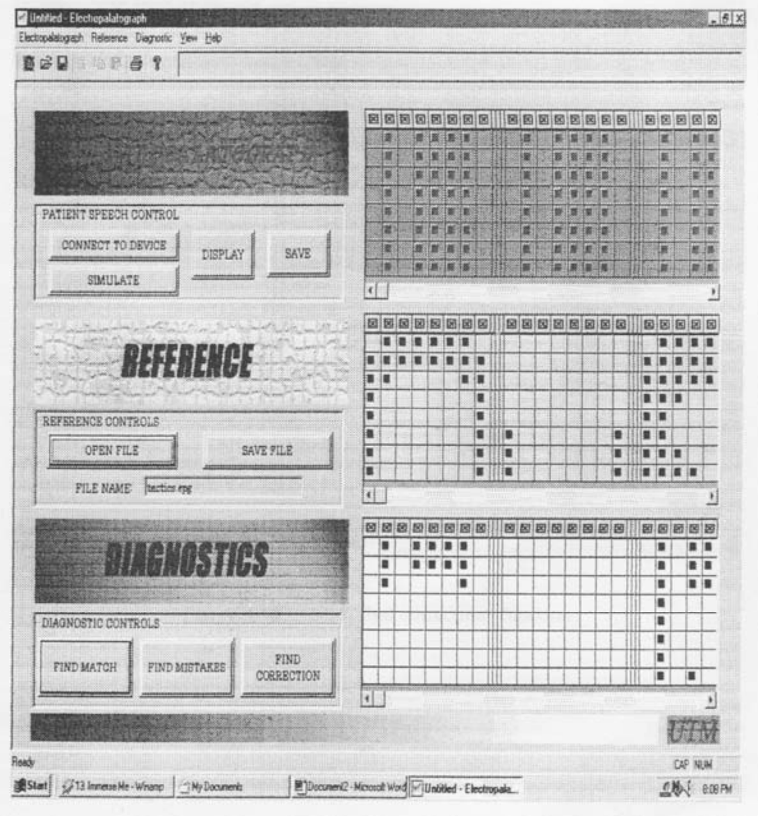
The diagnostic function requires both the input from the patient and the reference file. Fig. 7.13 will display the results obtained using the EPG Simulator and the reference file tactics. Then the button "find mistakes" is pressed.



FILE NAME: tactics.epg

Fig. 7.13 The "find mistakes" function

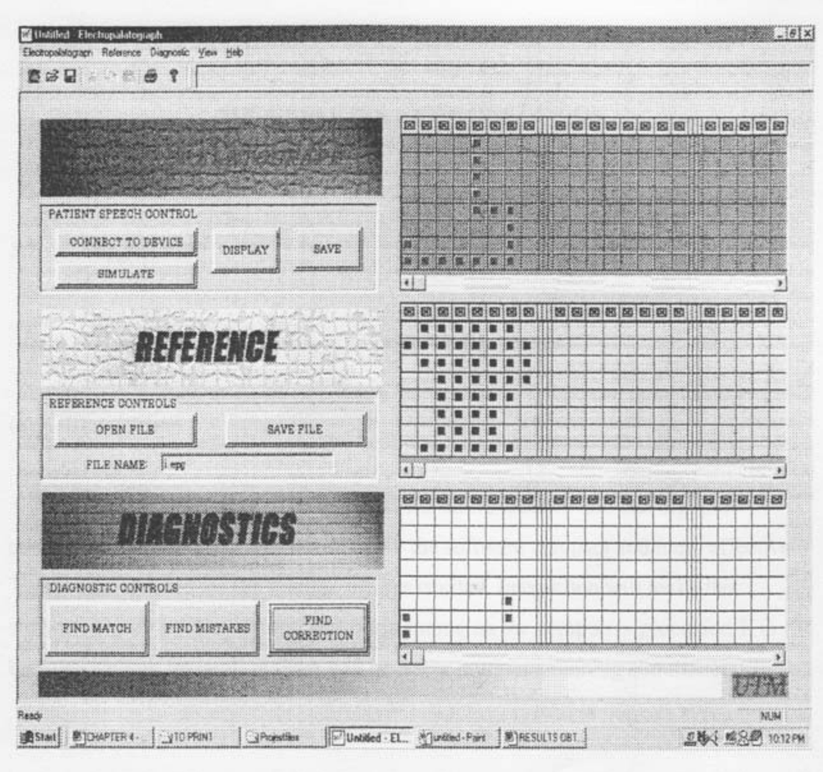
Example in Fig. 7.14 will display the result obtained using the driver with the pin 8, 3, 1 grounded and the reference file tactics. Then the button find match is pressed.



FILE NAME tactics.epg

Fig. 7.14 The ‘find match’ function

Example in Fig. 7.15 displays the results obtained using the EPG Simulator and the reference file ‘I’. Then the button find correction is pressed.



FILE NAME: i.epg

Fig. 7.16 The ‘find correction’ function

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8

A MODEL OF ELECTROGLOTTOGRAPH SYSTEM

Rubita Sudirman
Ching Jian Haur
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BACKGROUND

Speech has evolved over a period of tens of thousands of years as the primary means of communication between human beings. Since the evaluation of speech and of *homo sapiens* have proceed hand-in-hand, it seems reasonable to assume that human speech production mechanisms, and the resulting acoustic signal, are optimally adapted to human speech perception mechanisms.

There a lot of method to measure and analyse the speech production, there are Electropalatography (EPG), Accelerometer, Rothenberg Mask, Optical Tracking (Strain gauge), X-ray Microbeam (Magnetometer), Ultrasound, Electromyography (EMG), X-ray cine, Magnetic Resonance Imaging (MRI), Pressure Transducers, Respitrace, Photoglottography (PGG), Video, Electroglottography (EGG), Velotrace and Photoglossometry.

The Electroglottography, sometime also known as Electro-laryngography or Laryngography (trademark of Laryngography Limited) is a non-invasive method of measuring vocal fold contact during voicing without affecting speech production. The electroglottograph or known as EGG measures the variations in impedances to a very small electrical current between the electrodes pair placed across the neck as the area of vocal fold contact changes during voicing. This method was first developed by Fabre (1957) and influential contributions are credited to Fourcin (1971 with Abbertion) and Frokjaer-Jensen (1968 with Thorvaldsen). The computer unit will process the data and display the electroglottograpgh (EGG waveform) in real time then analyse by the pathologies or therapist. They can relate the waveform with the actual movement of vocal fold. The movement here means the closure and opening phase, maximum contact and maximum open between the flap of tissue. Commercially available for this devices are produced by Laryngography Ltd. (Since 1974), Synchrovoice, F-J Electronics, Glottal Enterprise and Kay Elemetrics Corporations.

Actually pathologies or speech therapist trained the patients to perform the non-medical evaluation of a voice disorder and execute a plan to improve voice. In additional the Ear, Nose and Throat department, Phoniatrics, speech scientists, phoneti響 and linguistics department, foreign language teachers and so on. They can interpret the EGG waveform and analyse the voice regularity, voice quality, pitch, loudness control, fundamental frequency, voice onset time, the effects of laryngeal co-articulation and phe-phonatory laryngeal.

ARTICULATORY

Speech is the result of a highly complex and versatile system of coordinated muscular movements. The involved structures are known as the articulators. Their movements are controlled neurologically. The articulators are the respiratory system, larynx, pharynx, velum, lips, tongue, teeth and hard palate.

The articulators discussed here will concentrate to larynx, because the Electroglottograph directly related to larynx or vocal fold. The larynx is located in the neck (trachea), it acts as a valve between the lungs and mouth, and as such it plays an essential role in eating and breathing. The “Adam apple”, seen most prominently on men, forms the front of the larynx. The vocal folds extend back from the Adam’s apple. The vocal folds are two flaps of tissue. Muscles can move the cartilages in order to adjust the position and tension of the vocal fold. The vocal fold serves 2 primary functions, there are to create voice or speech production and prevent foreign object that have slipped post the epiglottis from entering the lung. Here we will discuss the first function of vocal folds only. So, the segments with vocal folds vibrations are voiced and all others are voiceless.

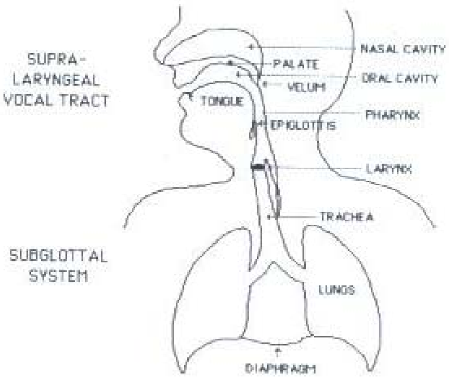

Fig 8.1 Articulators used in the production of speech sounds

SPEECH PRODUCTION

When the people produce the voice, the acoustic energy is produced; the air will passes from the lungs to the larynx and exhales. For many of the speech sounds, the opening and closing of vocal folds like a valve are use to interrupt and obstruct the flow of air, causing periodic of air, or phonation.

In more detail, speech is produced by inhaling, expanding the rib cage and lowering the diaphragm, so that air is drawn into the lungs. The pressure in the lung is the increased by the reverse process, contracting the rib cage and raising the diaphragm. This increased pressure forces the air to flow up the trachea (wind pipe). At the top of the trachea it encounters the larynx, a bony structure covered by skin containing a silt-like orifice, the vocal fold or glottis. The flow of air through the vocal fold causes a local drop in pressure by the Bernoulli effect. This drop in pressure allows the tension in the laryngeal muscles to close the vocal fold, thereby interrupting the flow of air. The pressure then builds up again, forcing the vocal fold apart, and enabling the air flow to continue. This cycle then repeats itself. The rest of the vocal tract, the oral and nasal passages, then acts as a filter, allowing the harmonics of the electroglottograph waveform which lies near the natural resonance of the tract to pass, whilst attenuating the others.

Some of the time the vocal fold are not vibrate there are when the vocal fold are held together, because there are no airs escapes from the lungs It also cause by when we open breathing, the vocal fold pulled as far apart as possible, voiceless and whisper.

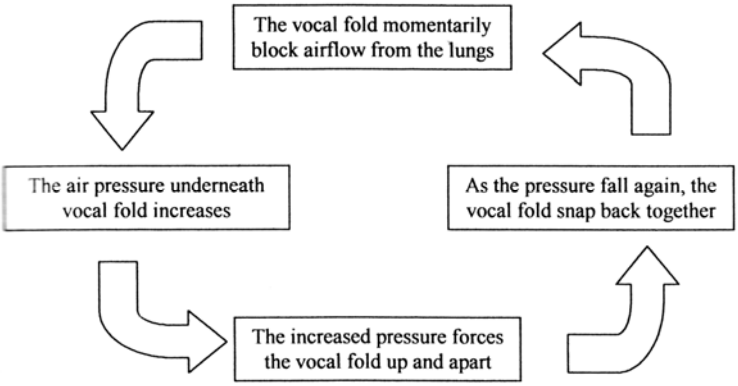
The vocal fold momentarily block airflow from the lungs
The air pressure underneath vocal fold increases
As the pressure fall again, the vocal fold snap back together
The increased pressure forces the vocal fold up and apart

Fig 8.2 The sequence of vibration

When vibration, each repetition of this cycle causes a "glottal pulse". The number of times this occurs in a second is the fundamental frequency of voice which for the men is around 125Hz, for woman are around 200Hz and for the children are around 300Hz. Normally the frequency of vibration will in the ranges between 60Hz and 400Hz. Differing length and mass of vocal folds lead to different fundamental frequencies of vibration. Breathy voice (murmur) will cause the vocal folds vibrate, but there is also a significant amount of air escaping through the glottis, cause turbulence. In creak, only the front part of the vocal folds is vibrating, giving a very low frequency (speaking at the lowest pitch). The creak and creaky voice are often call "laryngealization" or vocal fry".

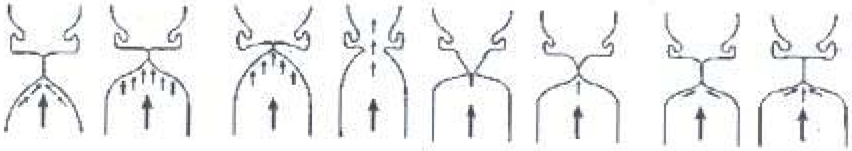

Fig 8.3 The speech cycle

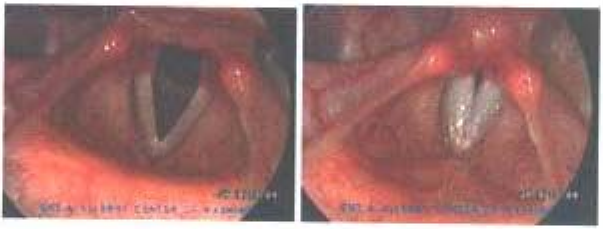

Fig 8.4 vocal fold open (left) and close (right) by endoscopies

When we try to produce the sounds "sss…" and "zzz…" or "fff…" and "vvv…" in alternation, the only change between each pairs is in the position of the vocal folds (open versus closed) and the voicing of the resultant sound (voiceless versus voiced).

According to the American Speech-Language-Hearing Association (ASHA), the normal voice is judge according to whether the pitch, loudness and quality are adequate for communication and suit a particular person. A person may use a pitch which is too high or too deep, too loud or too soft, too hoarse, breathy or nasal. Sometimes a voice may seem inappropriate for an individual, such as a high-pitched voice in an adult male.

The voice is in problem when the pitch, loudness or quality calls attention to itself rather than to what the speaker is saying. It is also a problem if the speaker experience pain or discomfort when speaking or singing.

INTERPRETING AND DESCRIPTION OF EGG WAVEFORM

This section will explain the EGG signal especially with respect to the shape of the waveform and to the time domain characteristics of the physiological features.

As mentioned before, the EGG signal is regarded as a correlate of the glottal area or the glottal opening width or the airflow pass the vocal folds. An experiment show an insulating strip was inserted between the vocal folds of an adult male during phonation to prevent electrical contact between them. There was no apparent effect of the production of an acoustic wave, but after the removal of the insulator the amplitude of the EGG signal increased. Additionally, the results enable the researcher to establish a linear relationship between the vocal folds contact area (VFCA) and the output of the electroglottograph. However, proper placement of the electrodes is very important since a slight shift might cause spurious effects in the recorded signal.

In this study, the increased vocal fold contact is consistently plotted upwards on the y-axis.

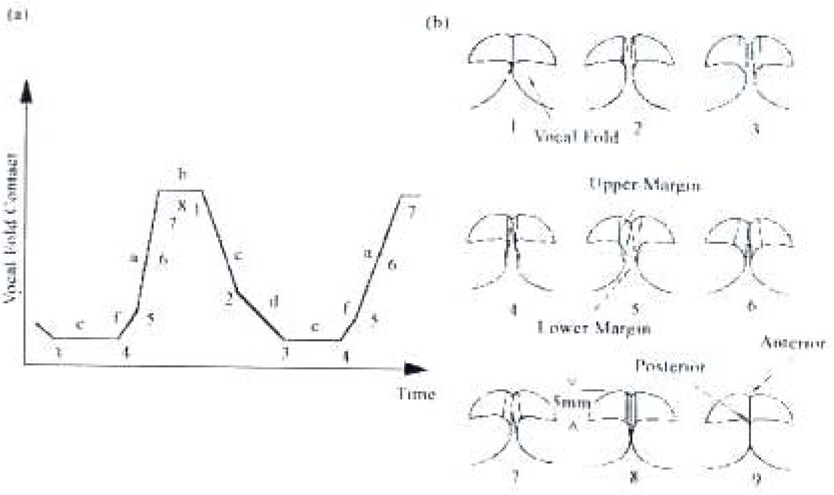

Fig 8.5(a) [Left] Phase of the idealized EGG waveform related to the vibration cycle
Fig 8.5(b) [Right] The model of the EGG waveform with annotated vocal folds movements phases.

The following paragraphs will discuss about the phase of the vocal fold contact. The six segments of the waveform above are denoted with the letters a, b, c, d, e, f, while instances of the fold movement are denoted with the number 1,2,3,4,5,6,7,8. When the vocal fold is open and it is ensured that it is no lateral contact between the vocal fold, the impedance is maximal and peak glottal flow occurs (segment e). The waveform in this segment is flat, with small fluctuations. Then the upper margins of the vocal fold make the initial contact (segment f). In the next phase of the movement (denoted as a) the lower margins come into contact and the vocal fold as a whole continue to close-zipper like. If the vocal fold closes very rapidly and along their whole length, the phase (f) and (a) become indistinguishable and consequently the slope of the closure phase (f) + (a) become steep (refer to Fig. 8.5(a)). The presence of this knee is typical for low to normal voice intensities and the slope of segment (f) is more gradual than the slope of (a).

Next phase is the glottal closure phase. Over large portion of the closing phase, the vocal fold adduct towards their medial position with little or no change in the length contact along the midsagittal line. Just prior to closure, the vocal fold contact area almost parallel with a narrow opening along their entire length. Closure occurs almost simultaneously along the entire midsagittal line. Thus, while the glottal area does not reflect this fact, the glottal closure is an abrupt phenomenon. This type of closure is typically seen as the pitch is raised.

During the next phase (indicate as b), the vocal fold remain in contact and the airflow is blocked. Like in phase (e), limited fluctuations of the impedance are observed. However, the waveform is not flat, but rather forms a smooth hill (or hump). During this phase contact increases until the maximum is reached and then slowly decrease again. The maximum of the EGG amplitude usually occurs after the instant of glottal closure. This is the result of the elastic collision of the tissue. This leads to mainly perpendicular vocal folds extension, which may cause the rounding of the EGG waveform, whose typical shape during the full contact phase is parabolic. If the contact area and its depth remain unchanged, the EGG is flat.

The opening and the open phase are describes analogously. In the process of vocal fold separation the contact between the fold starts to diminish and subsequently the lower margins of the vocal fold begin to separate, initializing the opening. Lower margin separation proceeds gradually during phase (c). Then the upper margins also begin to separate, resulting in acceleration in the growth of impedance (phase (d)) until the full opening is reached. The glottis grows in size during the phase. As the contact between the vocal fold is not maintained anymore, the EGG waveform does not reflect the glottal width or the glottal area. It also does not contain any information about the glottal flow.

THE PRINCIPAL OF OPERATION

The Electroglottograph system consists of a pair of electrodes, cable, EGG unit and a personal computer. A high frequency around 300kHz to 5MHz electrical constant current of small amplitude of voltage and amperage which physiologically safe and harmless passes between the two electrodes which will situate on the surface of the throat at the thyroid cartilage. Between the electrodes, the system will monitor the vocal fold opening and closure by measuring the variation in the conductance. The opening and closing of the vocal fold will vary the conductivity of the path between the electrodes causes amplitude modulated version of the transmitted signal (High frequency source). This amplitude-modulated signal is very small and it will be detected by an amplitude modulation detector then the detector circuit will demodulate this signal. The typical signal-to-noise ratio (SNR) of the demodulator is about 40dB. The demodulated AM waveform is then A/D converted and derives a waveform and stored in a computer.

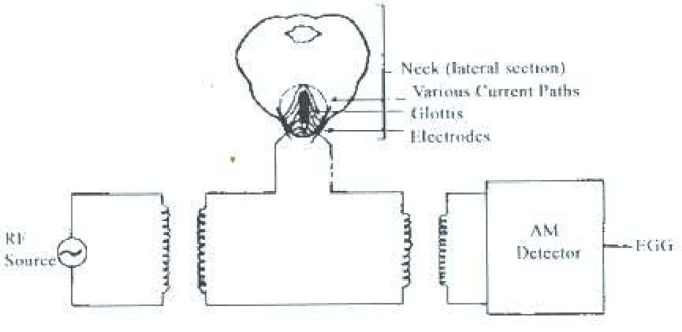

Fig 8.6 The Principle of the Electroglottograph Device

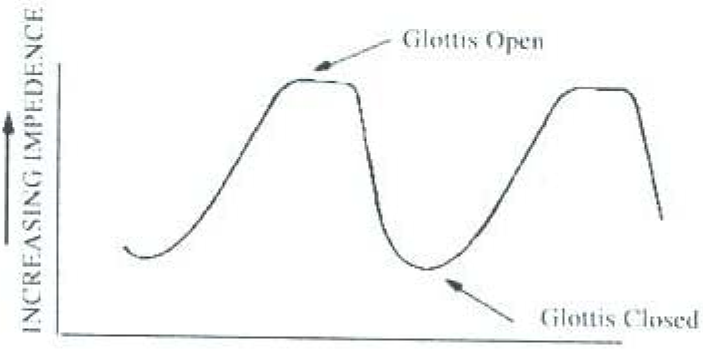

Fig 8.7 The detected Parameter

Mainly the movement of the vocal fold causes the rapid variation in the conductance, as they are separated; the transversal electrical impedance is high due to the fact that air impedance is much higher than tissue impedance. As they approximate and the contact between them increases, the impedance decreases, which result in a relatively higher current flow through the larynx structures. At the maximum contact the decrease is about 1% (up to 2%) of the total larynx conductance. According to Childers and Krishnamurthy the reason for the current modulation effect is a longer tissue passage for the radio frequency current when the glottis is open, since the total impedance of the tissue is a function of the length of the tissue passage. Generally the impedance is least for full fold contact because under this condition there are, in effect, many parallel equally conductive resistance paths between the electrodes. The combined total parallel resistance is less than the resistance of any one path. Therefore, it is reasonable to postulate that the tissue impedance seen by the EGG device is inversely proportional to lateral contacts area of the vocal fold.

The amplitude of the signal changes because of permanently varying vocal fold contacts. It depends on:

1. The configuration and placement of the electrodes
2. The electrical contact between the electrodes and the skin
3. The position of the larynx and the vocal fold within the throat
4. The structure of the thyroid cartilage
5. The amount and proportion of muscular, glandular and fatty tissue around the larynx
6. The distance between the electrodes.

It may happen that the impedance fluctuation caused by the vocal folds' movements is too weak to be registered. It also has to be noted that EGG signals of acceptable quality are harder to obtain from women and children than from men. This is related to the smaller mass of the vocal folds, the wider angle of the thyroid cartilage and different proportions between different types of tissues.

SINGLE-CHANNEL ELECTROGLOTTOGRAPH

The previous single channel Electroglottograph system are being used at many research laboratories, but except for rudimentary applications such as the measurements of vocal period, the technique has not been accepted for general clinical use. Basically there have 3 main reasons why the EGG is not use more commonly. According to Dr. Martin Rothenberg with his publication in Journal of Voice, the first is that there are many subjects for whom the previously available commercial units either year no output or one that is very noisy and/or very different from vocal fold contact area. The noisy or distorted waveform will disturb the user to indicate that waveform. Second, to obtain waveform that represent primarily the vocal fold contact area, previous unit require accurate placement of the electrodes with respect to the vocal fold. The practice of using extra guard-ring or reference electrode for reducing noise makes accurate placement more important, since if the glottis is mistakenly placed in the electrical field going to the guard or reference electrode, the closing of the vocal folds cam actually at to draw current away from the primary electrode and cause a partial signal inversion, or at least a distortion of the waveform. This cam easily tested experimentally be purposely shifting the contractor locations during the held vowel and looking fore changes in the waveform. Third, the electroglottography is not used more commonly because the various waveform features of interest to clinician have not yet been clearly charted. This is undoubtedly due in part to the first to problems, since it would be a waste of effort to document in detail the characteristics of a device that cannot be trusted.

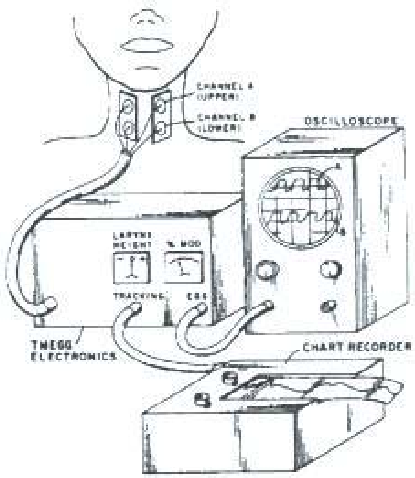

Fig 8.8 Various sources of noise or artifactual signal components that can be degrade electroglottograph performance as an indicator of vocal fold contact area

Fig 8.8 shows some of more significant noise with the schematic representations of a basic two electrode (signal channel) EGG, and below are the explanations about these noises.

LOW FREQUENCY ARTIFACT

A low frequency artifact can result from such factors as electrode movement of the muscularly controlled (nonvibratory) movement of the larynx and the articulators during continues speech. Since these movements vary little during each glottal cycle, their effect on the EGG waveform are theoretically removable by means of a high pass filter with a cut off frequency slightly below the voice fundamental frequency. If the filter is of the "linear phase shift" or "constant delay" variety (this description are mathematically equivalent), little distortion of the vocal fold contact area waveform will be introduced by the filter aside from a small known, fixed delay. Since low-frequency artifacts can be removed by filtering, this component has not been included in the illustrative EGG Waveforms in the figure above. However, some of the commercial EGG units make available an output containing lower-frequency components. The user, though, should keep in mind that these low-frequency outputs would always contain, to some degree, artifacts from other movements in or near the larynx-artifacts that are inherently not separable from the desired components.

RANDOM NOISE

The random noise such as a small amount of broad-band random noise, analogous to the "hiss" in a weak AM radio broadcast transmission and the "snow" in a weak television signal, is always introduced by the electronics in the transmitter and receiver circuitry and by RF energy from the environment that is picked up by the receiver circuit of the EGG unit. In the Fig 8.8, these random signal represented by R .Random noise can be difficult to identify in an EGG signal from a very hoarse or aperiodic voice, since the noise causes cycle-to-cycle variations in the signal that maybe similar in some respects to aperiodicities caused by irregular vocal fold movements. However, in most cases random noise is easy to identify in EGG waveform by it variability between glottal cycles. In addition if the EGG unit employs in automatic gain or label control circuit, the label in random noise in an EGG waveform is easy to measure by merely stopping the voice, as by holding the vocal folds closed against a positive lung pressure, and measuring the resulting broad-band noise, since the random noise components tend not to depend on the presence or absence of vocal fold vibrations.

VOICE-SYNCHRONOUS NOISE

The most inherently troublesome noise sources are those that are caused by the voice itself and therefore tend to produce EGG components that are synchronous week the desired vocal fold contact area signal, that are the same or similar in every glottal cycle. In the figure, these voice-synchronous noise components represented as S. This such noise can caused by any voice-generated physiological vibration that can affect the electrical impedance between the EGG electrode likes tissue vibrations at the skin-electrode interface, vibrations of the pharyngeal walls or tongue, vibratory movements of the false vocal fold or adjacent structures. Because of the mass of the tissue involved, the tissue vibrations causing the synchronous noise will tend to be smoothly varying at the vocal fundamental frequency, and as a result, voice-synchronous noise components will tend to be smoothly varying (have changes in the waveform that are less abrupt and much weaker high frequency harmonics) than the vocal fold contact area waveform. The voice-synchronous noise is the most difficult to separate from the true waveform.

Referring to Fig 8.8, A+R+S represent that EGG output with all the noise in small amplitude A and large amplitude A. Normally, the vocal fold contact area component maybe too small amplitude for some application when the modulation of the RF transmitter current caused by the variations in vocal fold contact falls much below about 0.1%, though the precise boundaries for various voices and application are not well determined at this time. On the other hand, with a well-design EGG unit, properly placed electrode and good electrode-skin contact, modulation percentages greater than about 0.2% generally produce an EGG output in which the vocal fold contact area component A tends clearly to dominate, as illustrated in the lowermost A+R+S trace. There have others possible distortion factors, like power line interference (easily identified by its synchronism to the power line frequency and generally removable by better electrical shielding and grounding or by moving to another test locations) or a non-uniform electrical field over the area of the vocal folds.

As a conclusion for signal channel EGG system, if the vocal fold contact area signal is too weak, it can result in an EGG waveform that is dominated by either low-frequency artifact, random noise or voice-synchronous noise in Fig 8.8. Because of the some neck physiologies, a weak signal component can be present even when the electrodes are not placed optimally. It is quite difficult to locate it, because the movement of the larynx or neck during the test procedure can disturb this propose. As the result, is difficult to place the electrodes in the best position, and the resulting the EGG signal will not sufficiently strong to trust as an adequate representation of the vocal fold contact area. At last, the new multichannel electroglottograph system is developed.

MULTICHANNEL ELECTROGLOTTOGRAPH

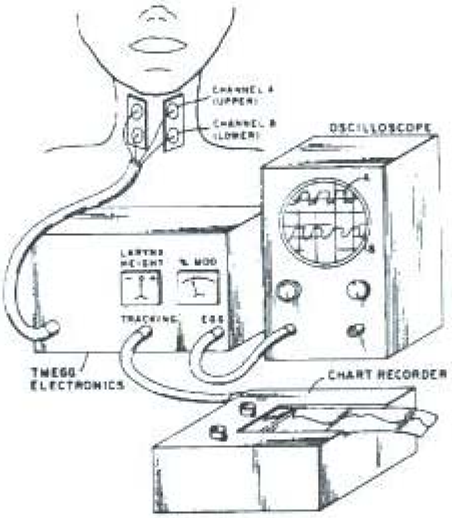

Fig 8.9 Two-channel tracking multichannel electroglottograph (TMEGG) having indicators for larynx height and percent modulations.

This Electroglottograph system used multielectrode arrays on each side of the neck to provide simultaneous EGG measurements at a number of neck locations. Each electrode pair, consisting of corresponding opposed electrodes, is connected to it respective transmitter and receiver, to constitute a channel, in this terminology. The electrodes in each array can be configured horizontally, vertically or in a two dimensional pattern. Since multichannel system employing a vertical array can be used to track the position of the larynx as it moves vertically during speech, so the vertical array will be discussed.

There have a major problem in implementing a multichannel EGG, it is the noise and distortion that can be generated by interference between the RF the electrical currents in the various channels. Though there are a number of methods that can be used to reduce such interference. One of the methods is technique of time-synchronizing the RF signal sources. In the two-channel vertical array prototype constructed using this principle, careful electrical design has resulted in a noise level in each channel that is no more than that of any pre-existing commercial design, even though somewhat smaller electrodes are used than is commonly the practice.

Thus, good performance is attained with electrodes small enough to be used in an array, this high level of performance has also been attained without the use of field-forming or reference electrode techniques that would distort the output from electrode pairs not at the level of the glottis. In addition, since the design provides separate electric fields for each electrode pair, more electrodes could be added without signal degradation. The frequency of the electrical current used, 2MHz, and the maximum voltage and current, to which the subject is exposed, about 1V and 10mA, respectively, are similar to that in other commercial units.

The important feature of the electrical design is that it does not employ the "feedback" or automatic level-adjusting techniques of some previous designs, so that the DC component of the demodulated receiver voltage can be calibrated in terms of the transverse impedance of the neck, and the ratio of the amplitude of the AC component of the TMEGG output in each channel to the DC output for the channel can be readily calibrated in terms of percent modulation of the electrode voltage. Thus, the percent modulation for each channel could be displayed for the operator as a measure of the efficiency of operation and signal reliability. To simplify the display, it should be sufficient to show only the percent modulation of the strongest channel (the greatest percent modulation). This indication of percent modulation could be compared with a range of percent modulation sufficient for proper operation, when such a range is developed by future research.

For the purpose of comparison, the output display separately using an oscilloscope. However, it is possible to automatically either combine the channel outputs or select between them, so as to produce one optimized signal for display or recording. If desired, amplitude normalization of this final output signal could be added, using some form of automatic gain control circuit. Naturally, the percent modulation measurement would be made using a signal that preceded any such normalization.

For use the TMEGG with the mutichannel display device, the user would normally position the electrode array for approximately equal amplitudes. Positioning for equal waveform amplitudes would be expected to place the electrode differences in the contact pattern of the vocal folds along their vertical dimension, in addition, the electrical field intensity from an electrode pair was significantly non-uniform over the vertical dimension of vocal fold contact. Equal waveform amplitude would also not indicate a centered glottal position if the physiology of the neck caused grossly different field intensities for each electrode pair at the plane aquidistant from each electrode pair. However, there is not evidence that either of these factors is significant in subjects tested to date.

An alternative positioning procedure, a relatively simple electronic circuit can be used to compare the output amplitudes and provide the user with a meter or bar graph indication of correct position. The meter in the Fig 8.9 labeled “Larynx Height”. When the meter is showing the center, it means that the trace A and B were of equal amplitude, and therefore that the vocal folds were approximately centered vertically between the electrode pairs. The electrical voltage applied to the larynx height meter could also be output as “tracking” signal that would trace vertical movement of the larynx during voice production. Since these vertical movements are much lower than the vocal folds vibrations, they can be recorded directly on a chart recorder having a frequency response flat to only 5 or 10 Hz. An approximate calibration of the tracking signal, as in terms of volts per millimeter larynx movement, is possible by means of a reciprocal techniques in which the larynx is held still during a constant vowel while the electrode are move vertically by some convenient increment, say 5mm, and the resulting variation in the tracking voltage is recorded. So as conclusion here, the multichannel EGG can be develop further, since it is better than normal or single EGG.

POWER SUPPLIES

For this project, the linear voltage regulators are used. Since most of the ICs used in this project need positive and negative supplies. The fixed positive and fixed negative voltage regulators start with 78XX and 79XX are used.

The capacitors are not always necessary, but to maintain the output in constant DC value, an input capacitor is used to prevent unwanted oscillations when the regulator is some distance from the power supply filter such that the line has a significant inductance whereas the output capacitor acts basically as a line filter to improve transient response.

The input voltage must be at least 2V above the output voltage in order to maintain regulation. These integrated circuits have internal thermal overload protection and short circuit current limiting features. Thermal overload occurs when the internal power dissipation becomes excessive and the temperature of the device exceeds a certain value. The heat sinks are functioning to reduce the heat from the power dissipation.

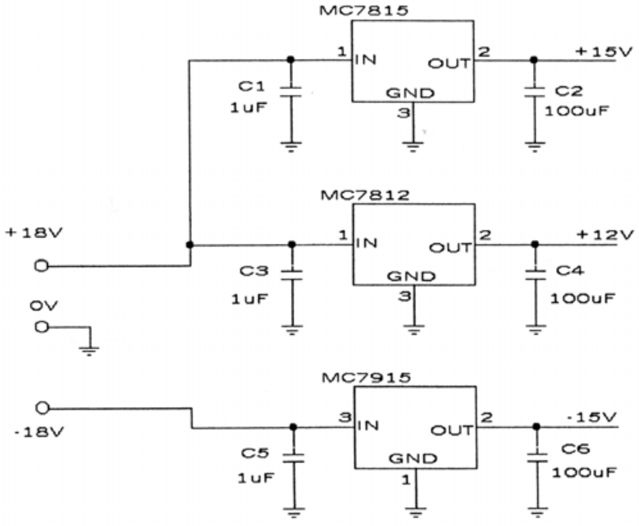

Fig 8.10 Power supplies unit

OSCILLATOR

Oscillator is an electronic circuit that operates with positive feedback and produces a time-varying output signal without an external input signal. The Wien-bridge oscillators are applied to generate the high frequency source. The Wien-bridge oscillator is one of the RC oscillators which can produce the sinusoidal output up to 1 MHz. It is by far the most widely used type of RC oscillator for this range of frequencies.

Fig 8.11 is the Oscillator in Hardware Simulation Model Circuit and Simulation System Circuit to generate high frequency source. The wide band op-amp LF351 used here can be viewed as a noninverting amplifier configuration with the input signal fed back from the output through the lead-lag circuit. From the principle of Wein-bridge oscillator, when the output voltage peaks at a frequency or called resonant frequency, at that point the attenuation of the circuit is one third if the same value of resistors and capacitors are used in lead-lag circuit. Since the closed feedback loop gain of oscillator must equal to 1, this mean the gain of amplifier should be equal to 3.

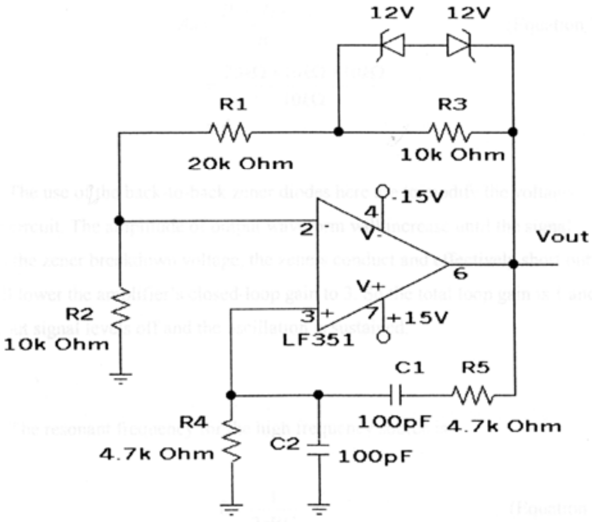

Fig 8.11 Wein-Bridge Oscillator for the Carrier Signal

To start up the oscillation, the close loop gain of amplifier must be more than three until the output signal builds up to a desired level. From the calculations:

$$A_{cl} = \frac{R_1 + R_2 + R_3}{R_2} = \frac{20\text{k}\Omega + 10\text{k}\Omega + 10\text{k}\Omega}{10\text{k}\Omega} = 4 \qquad (8.1)$$

The use of the back-to-back zener diodes here are to modify the voltage-divider circuit. The amplitude of output waveform will increase until the signal reaches the zener breakdown voltage, the zeners conduct and effectively short out R3 this will lower the amplifier's closed-loop gain to 3. So the total loop gain is 1 and the output signal levels off and the oscillation is sustained.

The resonant frequency for the high frequency source is:

$$f_r = \frac{1}{2\Pi RC} = \frac{1}{2\Pi(4.7k\Omega)(100\,pF)} = 338.6kHz \qquad (8.2)$$

Fig 8.12 is another circuit for the oscillator used in simulation system circuit, the IC used is UA741. All the parts are maintain the same except the resonant frequency, because this frequency need between the range 100Hz to 300Hz, since the vocal fold vibration (open and close) is around this range and depends on individual.

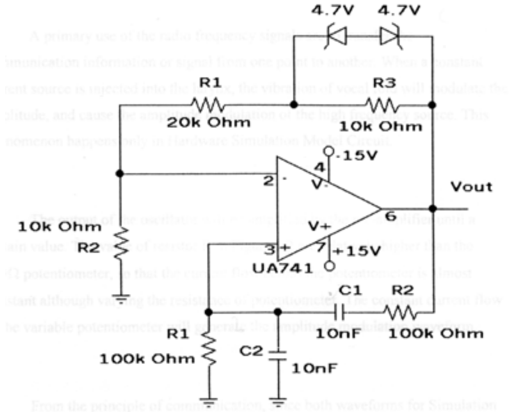

Fig 8.12 Wein-Bridge Oscillator for Modulating Signal

The resonant frequency by calculation from the Equation 8.1 for the Modulating Signal is:

$$f_r = \frac{1}{2\Pi RC} = \frac{1}{2\Pi(100k\Omega)(10nF)} = 159.2Hz \qquad (8.3)$$

AMPLITUDE MODULATION (AM)

A primary use of the radio frequency signals are to transfer the communication information or signal from one point to another. When a constant current source is injected into the larynx, the vibration of vocal fold will modulate the amplitude, and cause the amplitude modulation of the high frequency source.

The output of the oscillator will be amplified by the pre-amplifier until a certain value. The value of resistor R in Fig 8.12 is relatively higher than the 500Ω potentiometer, so that the current flow across the potentiometer is almost constant although varying the resistance of potentiometer. The constant current flow to the variable potentiometer will generate the amplitude modulation waveform.

From the principle of communication, since both waveforms for Simulation System Circuit are in sine wave, so that the equation for carrier signal is

$$V_c = E_c \cos \omega_c t = E_c \cos 2\Pi(339x10^3)t \tag{8.4}$$

and the modulating signal's equation in Simulation System Circuit is

$$V_s = E_s \cos \omega_s t = E_s \cos 2\Pi(159)t \tag{8.5}$$

so that the modulated signal in Simulation System Circuit will be

$$V_m = (E_c + E_s \cos \omega_s t) \cos \omega_s t \tag{8.6}$$

$$= E_c (1 + m \cos \omega_s t) \cos \omega_c t \tag{8.7}$$

which m is ratio of Es and Ee. The percentage of modulation is given as:

$$\%m = \left(\frac{E_s}{E_c} \right) 100\% \tag{8.8}$$

in frequency domain, the spectrum can be view as Fig 8.13:

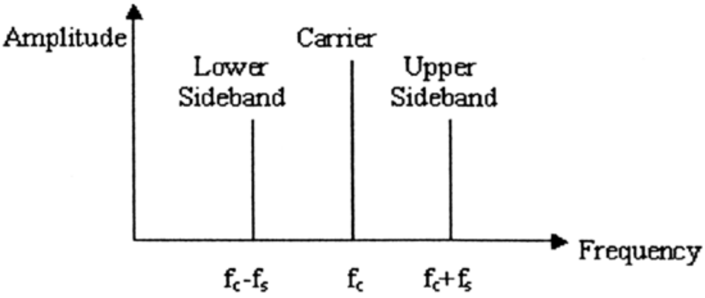

Fig 8.13 AM Spectrum in frequency domain

In the Simulation System Circuit, MC1496 is used as an amplitude modulator with a minor modification. The MC1496 is a monolithic balanced modulator which consists of an upper quad differential amplifier driven by a standard differential amplifier with dual current sources. The output correctors are cross-coupled so that the full-wave balanced multiplication of the two input voltages occurs. The output signal is a constant times the product of the two input signals.

INSTRUMENTATION AMPLIFIER

Instrumentation amplifier is widely used in medical electronic equipment such as in data acquisition systems where remote sensing of input variable required. The use of instrumentation amplifier in this model is to amplify small signals that riding on large common-mode voltages. The characteristics are high input impedance, high common-mode rejection, and low input noise. Low output offset and low output impedance.

The input impedance either differential mode or common mode of INA121 is up to 10^{12} Ω. This impedance is relatively much greater than the parallel resistance of potentiometer in Hardware Simulation Model Circuit, so that it will not affect the resistance of potentiometer and the waveform generated by the varying potentiometer. The gain of INA121 is determined by: $G = 1 + \frac{50k\Omega}{R_G}$, which R$_G$, is the external resistor.

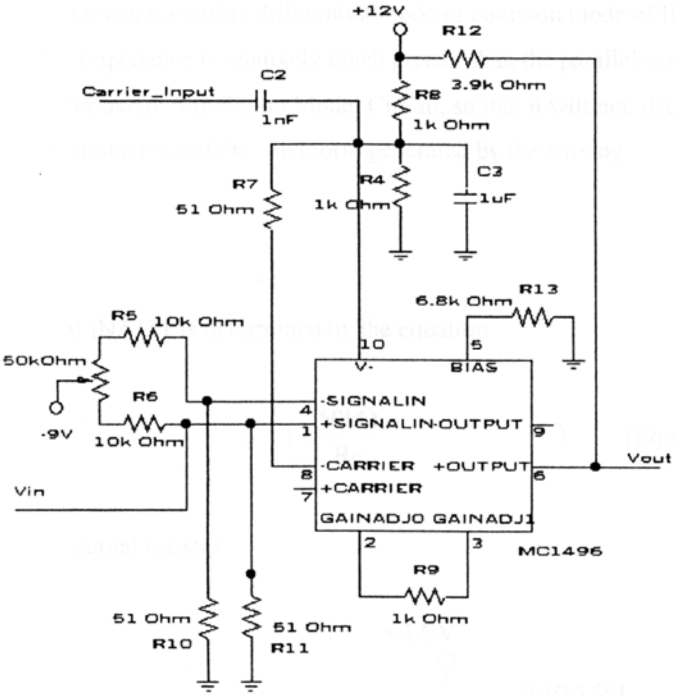

Fig 8.14 Amplitude Modulation circuit

AM WAVEFORM DEMODULATOR

The modulated signal containing the modulating signal and the carrier signal, For the AM waveform demodulator part, both of the circuit in this project (Hardware Simulation Model Circuit and

Simulation System Circuit) need to separate these two signals and the modulating signal is the signal which contains information of vocal fold contact area signal.

In the AM waveform demodulation circuit, the diode acts as a rectifier, which it can rectify only the positive side AM waveform. This positive side waveform is containing the DC value. To get the positive envelope from the positive side AM waveform, a pair of parallel resistor and capacitor is added after the diode. The value of R and C in parallel are determined by $f_s << \frac{1}{RC} << f_c$ where $RC = \tau$ or time constant. From the Fig 8.15, C discharges only slightly between carrier peaks and voltage v approximates the envelope of V_{in}. Finally C_1 acts as a DC block to remove the bias of the unmodulated carrier component. Since the DC block distorts low frequency components, conventional envelope detectors are inadequate for signals with important low frequency content.

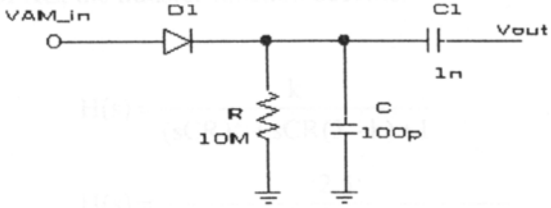

Fig 8.15 AM Envelope Detector

Theoretical calculation for frequency is $\frac{1}{\tau} = \frac{1}{\mathrm{RC}} = 1000\mathrm{rads}^{-1}$

So this 1000 rad s^{-1} is in the range of f_s and $f_{c.}$

RESULT AND DISCUSSION

The result of the high frequency oscillator (carrier signal) for Hardware Simulation Model Circuit and Simulation System is showed in the Fig 8.16. Calculated value of frequency is 338.6kHz, but the frequency which obtained from the result is 110kHz. The practical frequency is different from the calculation because the project is using protoboard with the high frequency; the stray capacitance exists between the conductors of the board. Besides, the resistors in used also have their own tolerance within certain percentage, so all of this will cause the resonant frequency to differ from the calculated value frequency.

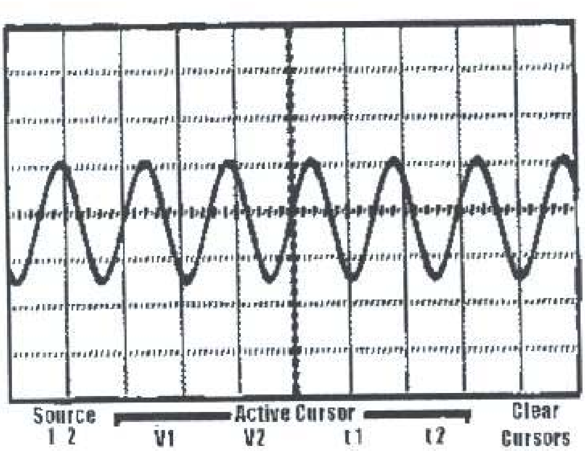

Fig 8.16 Output of High Frequency Oscillator (Carrier Signal) (110 kHz)

To generate the modulating signal in the Simulation System Circuit, another Weirs-bridge oscillator is built, the resonant frequency of this oscillator by calculation which represents the vibration frequency of vocal fold is 159.2Hz. In practical, the output of the oscillator is 130Hz. The frequency is not much different from the calculation because the frequency is low. Fig 8.17 shown the output of the oscillator.

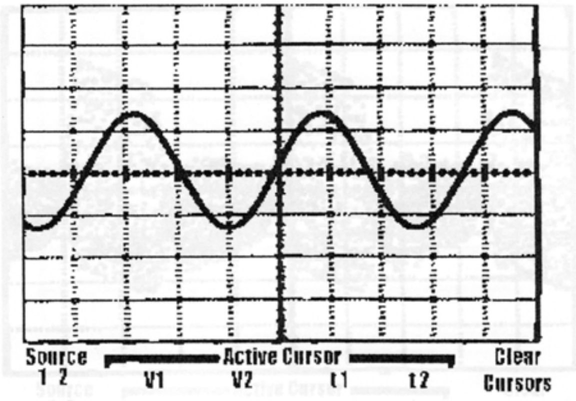

Fig 8.17 Output of oscillator (Modulating Signal) (130Hz)

The result of the AM modulation waveform is shown in Fig 8.18. This AM waveform is according to the modulating signal (130Hz) which carried by the carrier signal in 110 kHz.

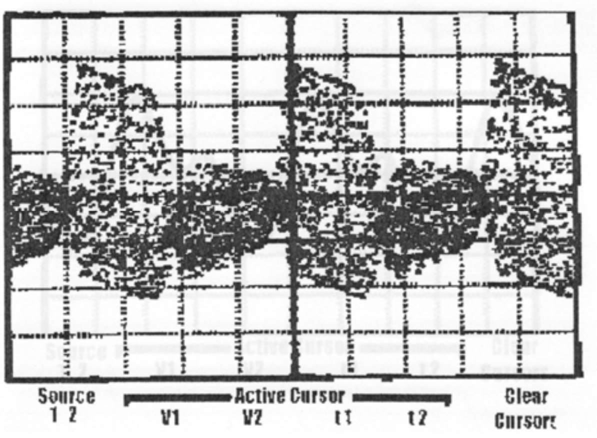

Fig 8.18 AM Modulated Waveform

The output of the project is the signal which represents the vocal fold contact area, so by simulating this model, supposedly the output here will get exactly same signal as the modulating signal which the signal before the AM circuit. But for this project, the shape of the output is not exactly same because of the capacitors discharge in the AM demodulator circuit. The time constant must be really effective to perform the original waveform. Besides that, after the demodulator, the output signal envelope with high frequency component, so the low pass filter is to reduce the high frequency component, then the waveform is shown in Fig 8.19. The output frequency is still maintained at 130Hz.

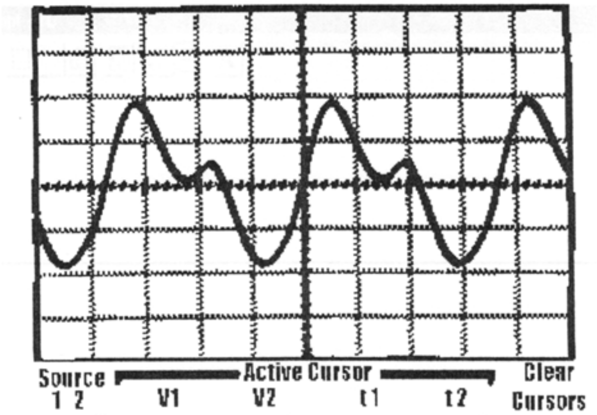

Fig 8.19 Output of the Simulation System (130Hz)

This output which captured from the oscilloscope is same as the output which displayed in the computer using PCL-816 with the written software. This means that the signal sent to the PC via ADC can display the graph using this software and software performs the conversion correctly. The output from the monitor is shown in Fig 8.22. This output is captured on the screen in DOS mode with the color inverted and this is the final output of the project.

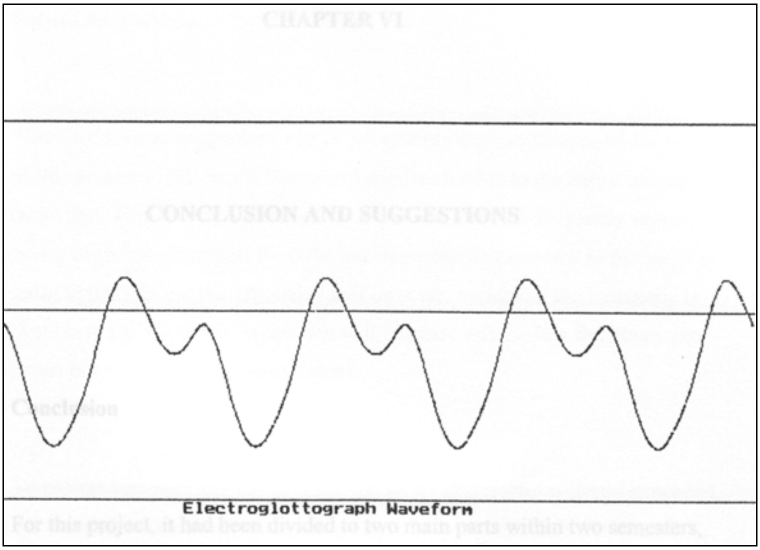

Fig 8.22 The Output From the Computer Screen

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9

NASAL AIRFLOW SYSTEM

Chiang Yok Peng
Rubita Sudirman
Khairul Nadiah Khalid

INTRODUCTION

Voice is a very important element throughout our life. Everyday we communicate with other people by talking, express our feelings by singing, laughing and shouting. However, with an inaccurate speech production, miscommunications or even misunderstanding can happened. Speech production requires a complex coordination of the articulators, which included the larynx, pharynx, velum, lips, teeth and hard palate, and also the tongue. Patients of inaccurate speech production normally were caused by accidents or since born or under other special reasons.

It was long ago since the scientists started to show their interest in speech rehabilitation. Researches have been done and finally they came out with the equipment called the nasal airflow system. This nasal airflow system works by comparing the patient's nasal airflow and voice reading with the normal sample provided by a normal speech person and displaying the results in a personal computer. Normally this system is helpful in speech therapy and also in singing teachers' studios.

An example of the nasal airflow system that is on the market now is shown in Fig. 9.1. Nasal Airflow System does not stand-alone. Typically, it is combined with Linguagraph (a clinical electropalatography system), Laryngograph (measures function of larynx) and also Videofluoroscopy (detects the movement of the velum and tongue).

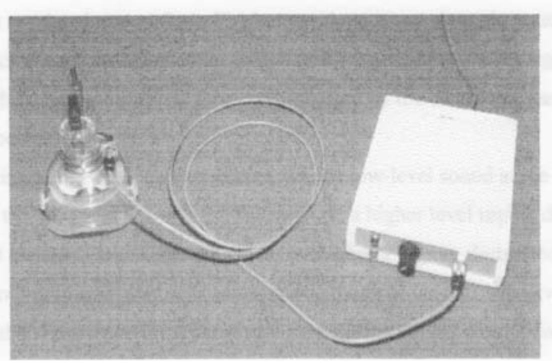


Fig. 9.1 Nasal Airflow System

NASAL AIRFLOW SYSTEM + LINGUAGRAPH

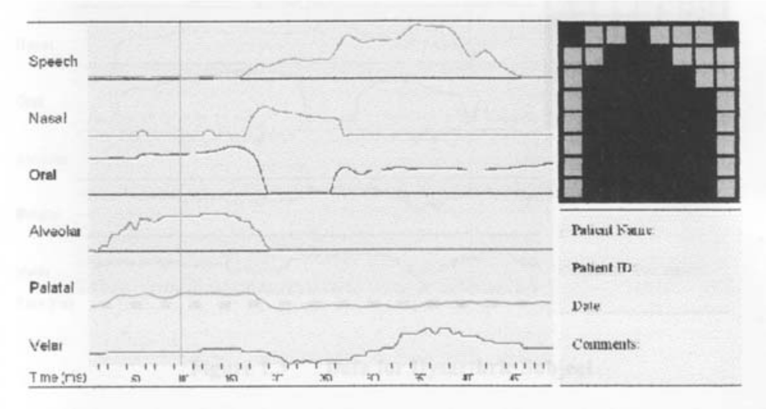
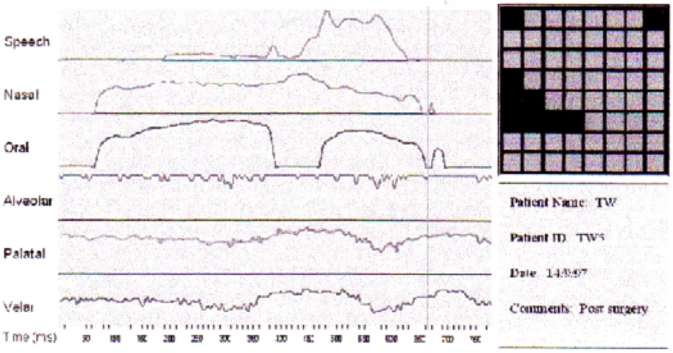


Fig. 9.2 Data from a normal speaker

Fig. 9.2 is a result for the word "smoke" produced by a normal speaker. The top trace is the envelope of the speech sound and the next two traces represent the nasal and oral airflow. The bottom three traces show the total lingua-palatal contact in each of the alveolar, palatal and velar regions. To the right, is a snapshot of the tongue contacts at the point indicated by the cursor and panel of patient data. Observe the speech waveform, we see low-level sound at the beginning, representing the voiceless fricative /s/, followed by a higher level region during the voiced, nasal constant, /m/. There is then an even higher region, during the voiced diphthong, ending in a smaller peak representing the final voiceless plosive, /k/. The nasal and oral airflow waveforms show oral flow during the /s/, nasal flow during the /m/, and oral flow during the remainder of the word, as expected.

The tongue contact waveforms show a build up of contact in all regions (but especially the alveolar region) for the /s/, a release for the /m/, and a build up of velar contact, during the vowel, in preparation for the final plosive /k/. Fine detail, such as the groove for the /s/, can only be seen in a complete contact pattern snapshot. This is provided at the cursor position (maximum contact for the /s/).

In contrast, Fig. 9.3 is the data for a dysarthric subject.



Patient Name: TW

Patient ID: TW5

Date: 14/3/97

Comments: Post surgery

Fig. 9.3 Data from a Dysarthric

Although the "Speech" waveform has a similar overall shape to the normal trace, the airflow and tongue waveforms are completely different. While the oral airflow stops during the nasal /m/, the nasal airflow persists throughout the word, except for a brief closure just prior to the final plosive /k/. Tongue contact, in the alveolar region, is virtually 100% at all times. In the palatal and velar regions, it is also high, falling slightly for the fricative /s/ and the final part of the diphthong. These results reflect this subject's impaired velar and lingual function.

NASAL AIRFLOW SYSTEM + LARYNGOGRAPH

The Fig. 9.4 illustrates Nasal Airflow System combined with the envelope of the output from a portable Laryngograph system.

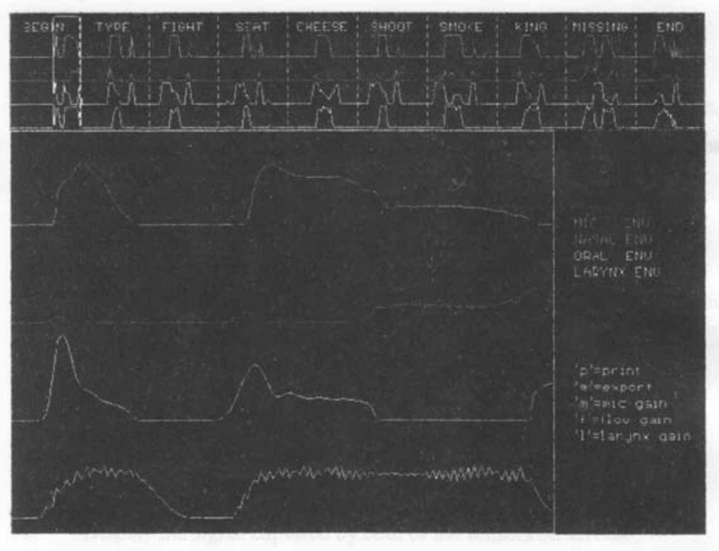


Fig. 9.4 Nasal Airflow System + Laryngograph

Here, the top trace shows the envelope of the resulting speech sound, the second and third traces are the nasal and oral airflow, and the bottom trace is the envelope of the voicing signal. Look at the sound trace (top), we initially see a pulse of sound energy, corresponding to the plosive /b/, falling off, during the first vowel.

This is followed by a short silence, during the closure for the /g/, after which there is another pulse for the plosive /g/, reducing slightly in level for the second vowel and reducing further for the final nasal consonant /n/.

The nasal airflow is virtually zero until the final, nasalised /n/, while the oral airflow peaks, during the two plosives and persists, at a lower level, during the vowels. The voicing (bottom trace) is present at all times, except during the brief silence, during the closure for the /g/. This is as would be expected.

THEORY OF RESPIRATORY SYSTEM AND SENSORS

Speech is the result of a highly complex and versatile system of coordinated muscular movements. The involved structures are known as the articulators. Their movement is controlled neurologically. Fig. 9.5 shows the respiratory system of human being.

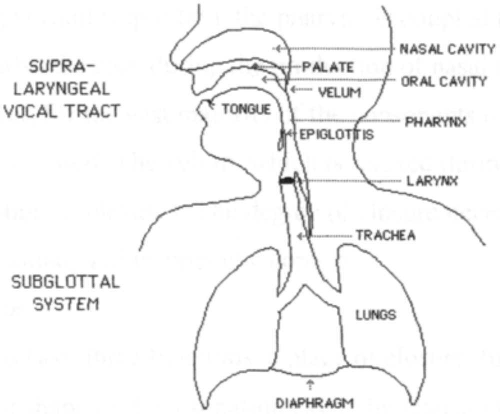


Fig. 9.5 Respiratory System

SPEECH PRODUCTION

Speech sounds are air pressure waves, which in the majority of cases, are powered by the expiratory phase respiration. During speech, a great deal of control is required.

i) The Larynx

Air passes from the lungs to the larynx. For many of the speech sounds, the vocal folds are used to interrupt the flow of air, causing pulses of air, or phonation. Differing length and mass of vocal folds lead to different fundamental frequencies of vibration: around 125Hz in men, 200Hz in women, and 300Hz in children. During speech, the frequency of vibration changes as pitch is changed in intonation.

i) The Pharynx

The air pressure waves then pass through the pharynx. Its role in speech is that of a resonating cavity, the dimensions of which can be altered, e.g. shortened or lengthened, by raising or lowering the larynx.

ii) The Velum

During normal respiration, the pharynx is coupled to the nasal cavity; this is also the case during the production of nasal consonants. However, for the vast majority of the consonants of English, the nasal cavity is closed. The velum, which is relaxed during normal respiration, is elevated. The degree of closure necessary is dependent on the sound, and its phonetic context.

iii) The Lips

The lips have three functions: a place of closure, further altering the size and shape of the resonation cavity by altering lip shape, e.g. /ں/, and a sound source, e.g. during /f/ - upper incisors ⟶ lower lip. Air passes through the gap under pressure, causing friction.

iv) The Teeth and Hard Palate

These are not active articulators, but essential contributors.

v) The Tongue

The most versatile of the articulators, being involved in the production of all vowels and the vast majority of consonants. The versatility of the tongue allows:

- Horizontal anterior/posterior movement of the body, blade, and tip
- Vertical superior/inferior movement of the body blade and tip
- Transverse concave/convex movement
- Spread/tapered contrast in the tongue blade and tip
- Degree of central grooving.

Different sounds require different tongue configurations. By altering tongue position and shape, the size of the oral cavity, and therefore its resonating characteristics, are changed.

If we take one example of a class of speech sounds – the plosive – these require vela-pharyngeal closure and stopping of the oral cavity. Air pressure builds up in the oral cavity and the rapid release of the closure, + or – voicing, causes the sound. For example, the voiceless alveolar /t/: the superior longitudinal muscle enables the tongue to form a seal around the alveolar ridge and edges of the hard palate. The velum rises as the levator palatini contracts, and closes against the pharyngeal wall. Expiratory air builds up pressure in the oral cavity and this is released as the tongue rapidly comes away from the alveolar ridge.

That's just one sound. When we consider that the average rate of speech is up to 4 syllable per second, each of which can contain anything up to seven consonants and a vowel sound, the complexity of articulator movement becomes apparent. It has been estimated that over 100 muscles are involved in the speech process and that their controlled co-ordination requires around 140,000 neuro-muscular events every second.

MICROPHONE

Sound is generated when we displace the normal random motion of air molecules. Sound travels as a wave, where it can travel through liquid and solid bodies, and other substances, but not vacuum.

There are three kinds of sound:

i. Ultrasound: Where sound exists above the threshold of hearing.
ii. Infrasound: Where sound exists below the hearing range.
iii. Normal sound: Where sound exists in the hearing range.

Sounds have three fundamental characteristics: pitch, timbre and loudness. Pitch is the fundamental or basic type of a sound and is determined by the frequency of the tone. Frequency of a wave is a measure of the number of complete waves per second; unit is hertz (Hz). Pitch is also classified to bass, midrange and treble. Timbre is the character of a sound, which enables us to distinguish between different musical instruments, including the voice while loudness overcomes the hearing characteristics by boosting the extremes sound ranges at low volume settings. Loudness is not the same with volume. In volume, we just increased all the tones in level.

Audio spectrum has a range of 20Hz to 20 kHz. Consequently, useful frequency range for microphones seems to be from about 50Hz to 15kHz. Although there are different models of microphones, they all do the same job. They are basically a collector of sound that transforms acoustical movements (the vibrations of air created by the sound waves) into electrical vibrations. This conversion is relatively direct and the electrical vibration can then be amplified, recorded or transmitted.

TYPES OF MICROPHONES

i) Carbon Microphone

The disadvantages of this microphone are it is noisy and will not respond to other than a limited range of sound frequencies and small compared to the wavelength of sound that reach it.

ii) Crystal Microphone

It is adequate for output sound without first considering its function. It has an unusual electrical property known as piezoelectric effect. Advantages are it supplies a moderately high output-signal voltage for a given sound input and the size is quite small, hence suitable for applications such as hearing aids. However, high temperatures and high humidity level can easily damage it. Its frequency response is too poor.

iii) Ceramic Microphone

The element used in this microphone is barium titanate. It is better than the crystal counterpart in heat, humidity and has high signal output.

iv) Dynamic Microphone

It consists of ribbon microphone and moving coil microphone. Ribbon microphone also known as velocity microphone. It is sensitive only to sounds coming at it from the front or back, not from the sides, supplies a bidirectional or figure-8 pickup pattern. For moving coil microphone, it develops a much greater output signal for a given sound pressure input. Bass-reflex speaker technique is sometimes included in dynamic microphones to extend and improve low-frequency response. Advantages of these microphones are: good transient response, a fair to good output signal level, smooth and wide frequency response, high reliability, and moderate cost.

v) Condenser Microphone

The output impedance of condenser microphones is extremely high. In order to avoid the use of connecting cables, the amplifier is built right into the microphone. The amplifier is more likely an impedance-changing device.

vi)Electret Microphone

It is just like condenser microphones, which require two voltages

– a voltage supply for the self-contained transistor amplifier or impedance converter and a polarising voltage for the condenser element. The example of the electret microphone is shown in Fig. 9.6.

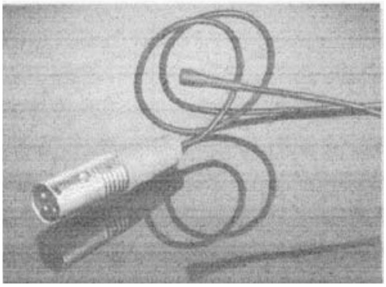


Fig. 9.6 Electret Microphone

WHAT IS MICROPHONE SENSITIVITY?

A microphone sensitivity specification tells how much electrical input (in thousands of a volt or 'millivolts') a microphone produces for certain sound pressure input (in dB SPL). If two microphones are subject to the same sound pressure level and one puts out a stronger signal (higher voltages), that microphone is said to have higher sensitivity. However, keep in mind that a higher sensitivity rating does not necessarily make a microphone better than another microphone with a lower sensitivity rating.

WHAT IS “Db SPL”?

The term "dB SPL" is a measurement of Sound Pressure Level (SPL) which is the force that acoustical sound waves apply to air particles. As a person speaks or sings, SPL is stronger near the mouth and weakens as the acoustical waves move away from the person. As reference levels, 0 dB SPL is the most quiet sound human can normally hear and 1 dB is the smallest change in level that the human ear can detect. For comparison, at 3 feet, speech conversation level is about 60 dB SPL and a jackhammer's level is about 120 dB SPL. 74 dB SPL is typical of the sound intensity 12 inches away from a talker. 94 dB SPL is typical of the sound intensity 1 inch away from a talker.

THERMISTOR

The word thermistor is actually a contraction of the words "thermal resistor". It is an electronic component that exhibits a large change in resistance with only a small change in temperature. It is constructed of Ge, Si, or a mixture of oxides of cobalt, nickel, strontium, or manganese. This predictable change in resistance as temperature changes is the basis for all applications of thermistors. The thermistor sensors are fabricated by forming a powdered semiconductor material, compressed between two conductive surfaces, which support the 2 terminals. It is usually monitored with a bridge circuit and then the variation are amplified by a known factor and expanded into a standard range, so to cover the entire useful temperature excursion.

Thermistors can be ranged in size from 3-mm to 22-mm in diameter. The advantages of thermistors over other forms of thermal sensor are for the following reasons:

i. Supply an alternative, relatively low cost to typical thermometer
ii. Enable faster measurement with highly superior accuracy.
iii. Large coefficient and large range of resistance values available.
iv. Able to operate over a wide temperature range in a solid, liquid or gaseous environment.
v. Adaptable size and shape for a wide variety of mechanical environments ability to withstand electrical and mechanical stresses.

Thermistors are widely used in the following application: fan control, Temperature sensing, circuit protection, temperature control and indication and compensation

The compound employed will determined whether the device has a positive or negative temperature coefficient. If a resistance value of the thermistor increases with the temperature, the thermistor is of the PTC type (**P**ositive **T**emperature **C**oefficient) and if a resistance value of the thermistor decreases with the temperature, the thermistor is of the NTC type (**N**egative **T**emperature **C**oefficient).

There are, fundamentally, two ways to change the temperature of the device: internally and externally. A simple change in current through the device will result in an internal change in temperature. A small applied voltage will result in a current too small to raise the body temperature above that of the surroundings. In this region, the thermistor will act like a resistor and have a positive temperature coefficient. However, as the current increases, the temperature will raise to the point where the negative temperature coefficient will appear.

An external change would require changing the temperature of the surrounding medium or immersing the device in a hot or cold solution. The variation law connecting the resistance to the temperature value is not linear but approximated to an exponential law, *which* can be presented on a logarithmic range:

$$R_t = R_o - e^{B(1/T - 1/T_o)} \tag{9.1}$$

where R_t = Resistance of thermistor
R_o = Nominal Resistance of thermistor
B = Material Constant
T = Thermistor Body Temperature
T_o = Nominal Temperature of Thermistor

The examples of the different kind of thermistor are shown in Fig. 9.7.

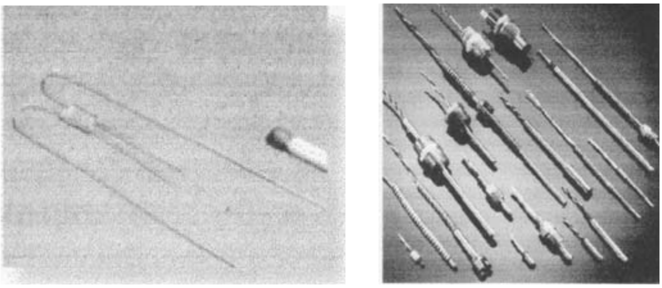


Fig. 9.7 Thermistors

NTC THERMISTOR

Commercial NTC thermistors can be classified into two major groups, depending upon the method by which electrodes are attached to the ceramic body. The first group consists of bead type thermistor, where they have platinum alloy lead wires, which are directly sintered into the ceramic body.

Bead type thermistors includes the following: Bare Beads, Glass Coated Beads, Ruggedised Beads, Miniature Glass Probes, Glass Probes, Glass Rods and Bead-In-Glass Enclosure.

The second group of thermistors has metalled surface contacts. All of these types are available with radial or axial leads as well as without leads for surface mounting or mounting by means of spring contacts.

Metalled surface contact thermistor include the following: Disks, Chips (Wafers), Surface Mount, Flakes, Rods and Washers.

PTC THERMISTOR

As NTC thermistor is more popular-use than PTC thermistor, thus discussions on PTC thermistor is not included in this literature review. The characteristics of a representative thermistor with a negative and positive temperature coefficient are provided in Fig. 9.8.

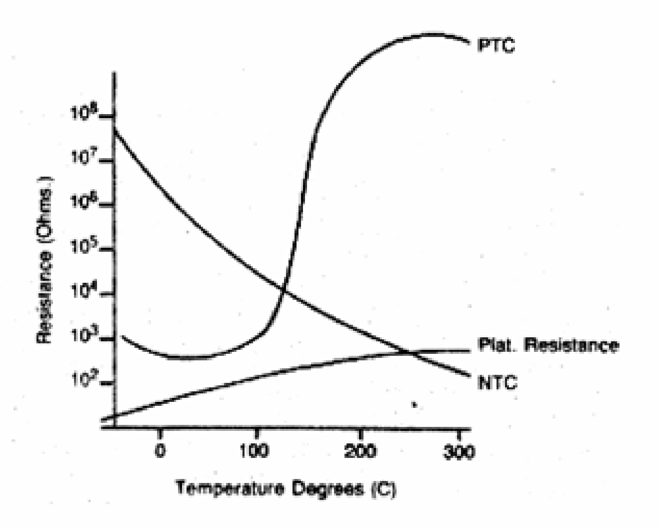


Fig. 9.8 NTC and PTC Characteristics

BASIC REQUIREMENT FOR NASAL AIRFLOW SYSTEM

As microphone and thermistor are used as sensors to detect the human's nasal flow and speech voice, it is important for us to select the suitable component to meet the specification. For microphone, it is preferred to be omni-directional where it can pickup sounds from all directions. Electret condenser made microphone will give better sensitivity and the range of frequency would be from 60Hz – 10kHz.

The characteristic of the thermistor will be with negative temperature coefficient, temperature range of 0 – 80°C, accuracy of +/- 0.01 'C and fast time response where as soon as the thermistor detected the temperature change, it will straight away give the result of the changes.

HARDWARE DESIGN

The design of each circuit in block diagram of nasal airflow system is shown in Fig. 9.9. The thermistor's circuit begins with a thermistor situated in a Wheatstone Bridge, the signal generated will then go to the differential amplifier. The signal generated from the microphone will go to a two-stage pre-amplifier, afterwards the signal will be amplified again and lastly is the filtering process. Both signals obtained from the sensors will then be connected to A/Dl converter where waves will be displayed on the computer.

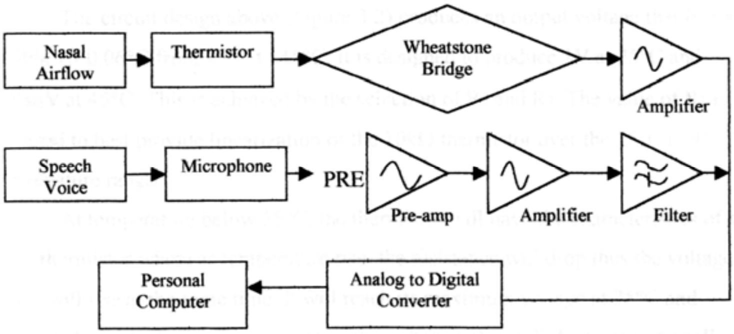


Fig. 9.9 Hardware Block Diagram

THERMISTOR CIRCUIT

Wheatstone Bridge

The function of Wheatstone Bridge in voltage mode is to produce a voltage output that varies linearly with the temperature, utilize the NTC thermistor as the active leg in the Wheatstone Bridge. The circuit in Fig. 9.10 produces an output voltage that is linear within +/- 0.06°C from 25°C to 45°C. It is designed to produce 1V at 25°C and 200mV at 45°C by selecting the value of R_2 and R_3. The value of R_i is selected to best provide linearization of the 10kQ thermistor over the 25°C to 45°C temperature range.

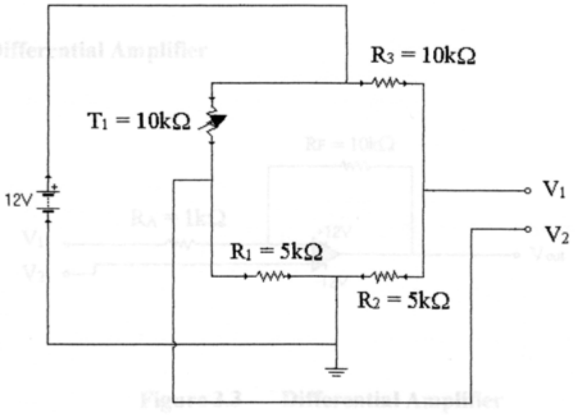


Fig. 9.10 Wheatstone Bridge

At temperature below 25°C, the thermistor will have the characteristics of a PTC thermistor; as temperature rise, the resistance will drop thus the voltage value will rise at the same time. It will reach its maximum voltage at 25°C and afterwards, as the temperature increase, the voltage value will drop proportionally. The difference of resistance in the bridge circuit is determined using equation (9.2).

$$\frac{T_1}{R_1} = \frac{R_3}{R_2} \tag{9.2}$$

Differential Amplifier

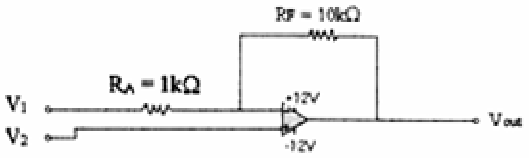


Fig. 9.11 Differential Amplifier

The differential amplifier is an extremely popular amplifier that is used nowadays. Note that the amplifier has two separate inputs and one output. The inputs get the signal supply from the differential voltages that generated due to resistance changes at the Wheatstone bridge circuit.

When opposite signals are applied to the inputs, the process of amplifying with the gain of 10 will be done. Let's say if the input signal has the value of 500mV, then the output voltage will be 5V.

The gain, A is obtained by:

$$A = \frac{R_F}{R_A} = \frac{10k\Omega}{1k\Omega} = 10 \tag{9.3}$$

MICROPHONE CIRCUIT

Pre-Amplifier

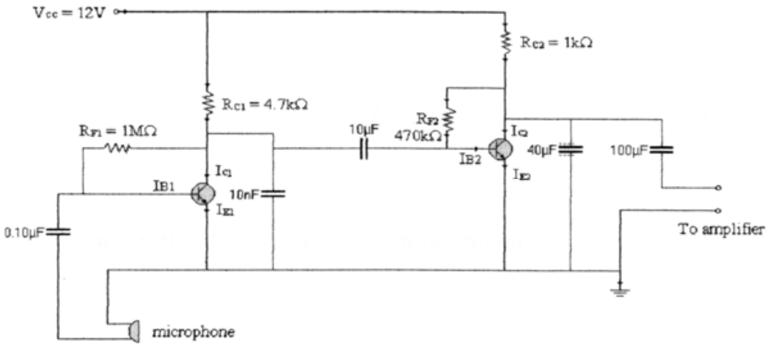


Fig. 9.12 Pre-Amplifier

This circuit in Fig. 9.12 is used to give out a microphone pre-amp stage to an amplifier, which will power the signal. The NPN transistors used are ECG123A. The collector feedback network employs a feedback path from collector to base to increase the stability of the system. It operates in much the same way as the emitter-bias configuration. To obtain the gain of amplification of each stage, one must step by step do the following calculation. First, the base current value of the first stage, I_B must be find.

$$I_B = {V_{cc} - V_{BE}} \Big/ {R_F + \beta R_C} \tag{9.4}$$

P has the same value as hF'E which is the small signal current gain. 0 is obtained from the data sheet that is provided from the manufacturer. After I_B is obtained, then I_E, the emitter current can be calculated.

$$I_E = (\beta + 1) I_B \tag{9.5}$$

The next step is to calculate the r_e of the circuit.

$$r_e = \frac{26mV}{I_E} \tag{9.6}$$

And finally the gain desired:

$$A = \frac{-4.7k\Omega}{r_e} \tag{9.7}$$

As for the second stage, same step is followed. The difference is that for Equation (9.7), the 4.7kΩ resistor is replaced by 1 kΩ.

Inverting Amplifier

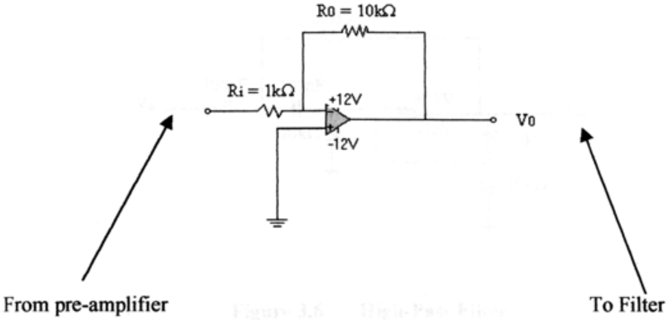


Fig. 9.13 Inverting Amplifier

The most widely used constant gain amplifier circuit is the inverting amplifier, shown in Fig. 9.13. The output is obtained by multiplying the input by a fixed or constant gain, set by the input resistor and feedback resistor – this output is also being inverted from the input. The input signal generated from the pre-amplifier is applied to the inverting (-) input while the non-inverting (+) input is grounded.

Referring to the circuit in Fig. 9.13, gain, A is calculated as:

$$A = -\frac{R_F}{R_A} = -\frac{10k\Omega}{1k\Omega} = -10 \tag{9.8}$$

The negative value of A indicates that the output signal is inverted (phase shift by 180^o).

High-Pass Filter

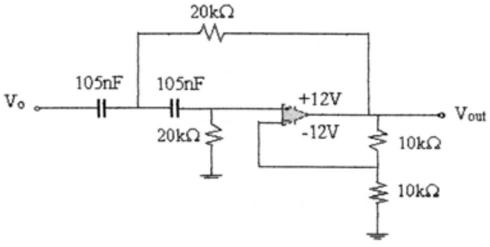


Fig. 9.14 High-Pass Filter

A high pass filter is one that significantly attenuates or rejects all frequencies below f_c and passes all frequencies above f_c. The critical frequency is the frequency at which the output voltage is 70.7 percent of the passband voltage, as shown in Fig. 9.15.

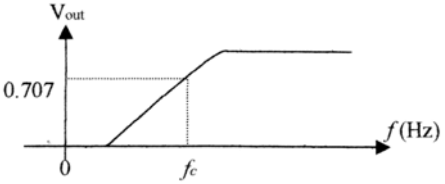


Fig. 9.15 High-Pass Filter Response

The circuit shown in Fig. 9.14 is a second order high pass filter. The critical frequency, f_c is calculated by the formula $fc = 1/2\pi RC$ assuming the two capacitors have the same value, as well as the resistors. The circuit designed has the critical frequency of:

$$\begin{aligned} \text{fc} &= 1 / 2\pi(20\text{k}\Omega)(10\mu\text{F}) \\ &= 76\,\text{Hz} \approx 80\,\text{Hz} \end{aligned}$$

RESULTS AND DISCUSSION

The waveform results from the hardware unit, which displayed on the personal computer, are discussed in this section. One thing that has to be mentioned is the signal supposed to be generated from microphone and thermistor is being replaced by signal generated from the function generator. This is because by the time I received those sensors, the time left for me before the actual presentation is just left not more than two weeks. As the microphone and thermistor being examined together with the rest of the circuit design, no signal is obtained at all from these sensors. Due to time limitation, further troubleshooting cannot be carried out and thus finally, signal from function generator as replacement has been made.

Another is about the pre-amplifier of the microphone. Firstly, this preamplifier was not constructed at all because the ICs: SSM2017 and OP275G was not received from the manufacturer even though orders have been made due to stock shortage. SSM2017 is a low noise pre-amplifier specially made for audio amplification where noises from the environment are being reduced to the very minimum effect. More information on this chip can be referred to Appendix 7. OP275G is just a JFET/bipolar amplifier.

The circuit of pre-amplifier shown at Fig. 9.4 is provided by Dr. Jasmy two days before the presentation. The circuit has been constructed and tested. It seems that the circuit can worked but the output waveform obtained is different from the expected result. Further troubleshooting could not be carried out and thus, at the end, the waveform results displayed on the personal computer are not discussed here.

MICROPHONE'S RESULT

The input wave is a sinus wave with the amplitude of 0.6V.

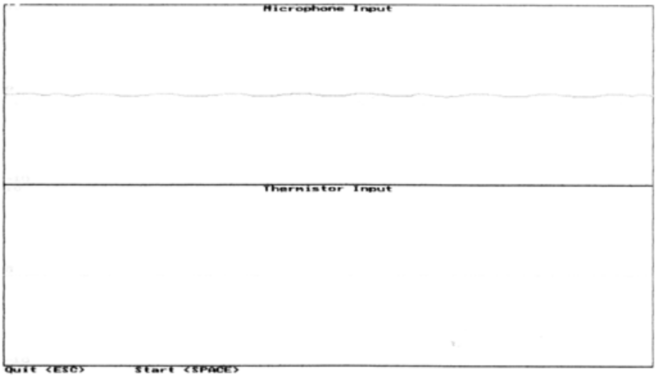


Figure 9.16 Microphone's Input

After the stage of amplification with the gain of 10, the amplitude of signal became 5.75V, approximate value of the theory. The theory value of the signal is 6V.

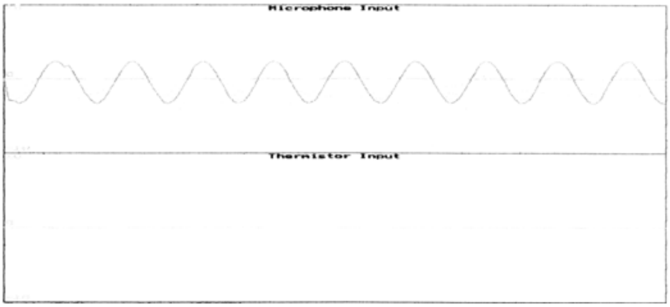


Figure 9.17 Microphone's Result after Amplification

At the last stage, the signal wave under 80Hz has been filtered and the amplitude of the signal is amplified again by the gain of 2.

Finally, the peak to peak voltage value became approximately 12V.

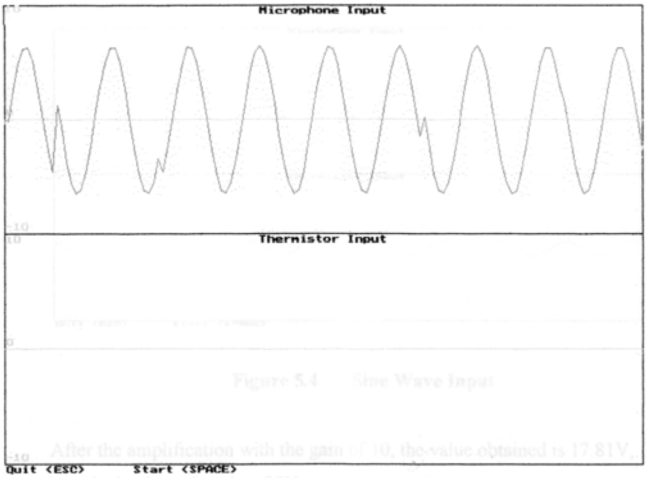


Figure 9.18 Microphone's Result after Filtration

Regarding the filtering process, this 12V voltage can only be obtained after 80Hz as steady-state characteristics has been achieved. For frequency below 80Hz, waveform can still be obtained but with the voltage value less than 12V. For frequency that is less than 20Hz, the waveform is totally been cut off. This incident happened because the filters that were build are only a two-stage filter, where the slope after the critical frequency exists. If we truly want the frequency below 80Hz been cut-off immediately, where the frequency response has the characteristics of a step function, then multistage filter must be built to improve the accuracy.

THERMISTOR’S RESULT

The input waveform is a sinus wave with the peak to peak amplitude of 2V.

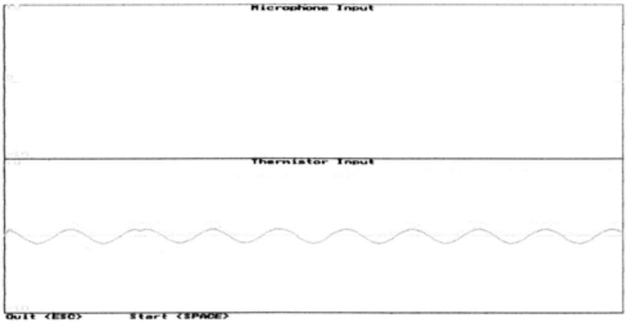


Figure 9.19 Sine Wave Input

After the amplification with the gain of 10, the value obtained is 17.81V, approximately the theory's value, 20V.

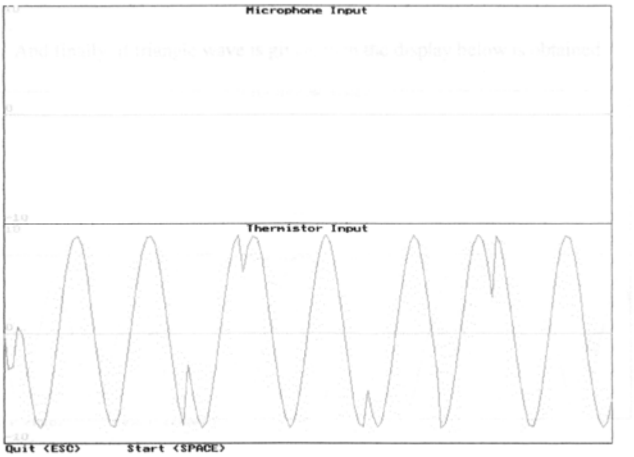


Figure 9.20 Sine Wave’s Result after Amplification

If the input signal is the square wave signal with the peak to peak voltage of 2, then the output voltage shown below will be generated.

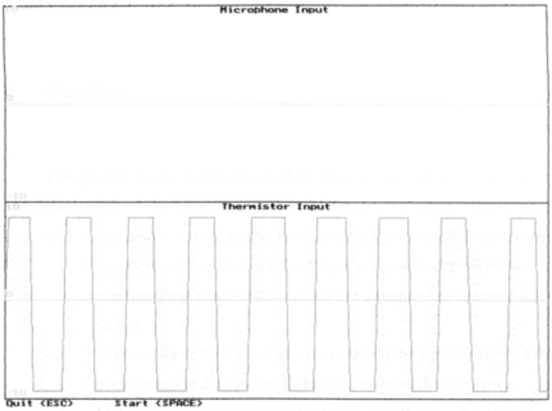


Figure 9.21 Square Wave's Result after Amplification

And finally, if triangle wave is given, then the display below is obtained.

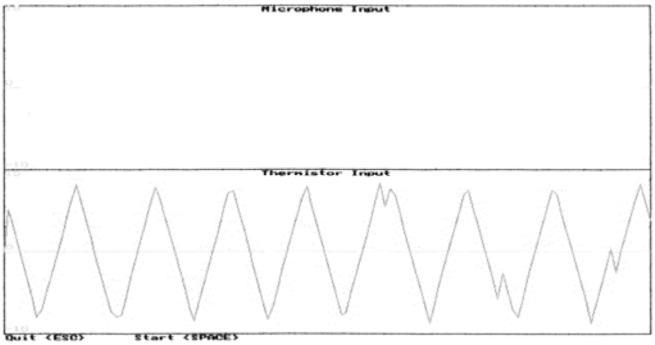


Figure 9.22 Triangle Wave's Result after Amplification

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